Immigration Policy and Equity Returns: Evidence from the H-1B Visa Program

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Abstract

I show that firms' access to skilled immigrant labor is an important determinant of the cross-section of equity returns. Using a comprehensive set of data on H-1B visa petitions, I construct an occupation-level measure of labor market competition between skilled immigrant and local workers. I find that stocks of firms in high-competition industries – those with a high share of labor for which skilled immigrants are close substitutes – outperform their peers with a low share. I show that this premium is explained by firms' differential exposures to priced immigration policy shocks that shift the supply of skilled immigrant labor. Based on evidence from the 2003 H-1B legislative cap reduction as a natural experiment, I show that these shocks differentially impact wages at the occupation-level, leading to an asymmetric effect on firms' cash flows through labor expenditure.

Keywords: Cross-Sectional Equity Pricing, Immigration, Human Capital, Wages, Financial Markets and the Macroeconomy

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Immigration policy is under scrutiny in many developed economies. The central question in the ever-growing economic debate on immigration is whether it benefits or harms the labor market outcomes of domestic workers. One side of this debate states that companies exploit immigration programs to replace native workers with lower-paid foreign workers. The other side views immigration as a means to promote innovation and growth by facilitating firms' access to talent that would otherwise be extremely costly to attract or train. A common assumption in both of these arguments is that firms benefit from access to immigrant workers with desired skills, as they are substitutes for an otherwise costly native labor.

Recent studies have documented the economic importance of skilled immigration programs as one of the main channels through which firms obtain human capital from the international labor market. To provide an example, Peri, Shih, and Sparber (2015) estimate that 10% to 20% of the annual productivity growth in the U.S. between 1990 and 2010 is attributed to the foreign engineers and scientists that were admitted to the U.S. under the H-1B visa program. At the firm level, access to skilled immigrant labor force is shown to be an important determinant of firms' future innovative activities (Ashraf and Ray (2017)) and investments (Xu (2017)). A natural question that arises in light of these findings is whether policies that affect firms' ability to hire workers through immigration are a source of macroeconomic risk that is priced in the cross-section of stock returns. The study presented in this paper addresses this question.

I show that firms with greater exposure to immigration policy shocks, as measured by the extent to which they can benefit from high-skill immigration, command a higher risk premium. Specifically, firms in industries with a high share of labor for which immigrant skilled workers are close substitutes generate significantly higher annual abnormal return than those in industries with a low share. I provide an explanation for this finding in the context of a search and matching framework, where firms are heterogeneous in the extent to which the availability of immigrant workers affects their chance to hire their desired skilled workers. In this setting, immigration policy shocks differentially affect the cash flow of firms depending on their reliance on occupations in which immigrants are competent. In other words, the exposure to immigration policy shocks is dictated by each firm's occupational composition.

Occupations are not homogeneous with respect to the combination of skills they require. Some jobs require high levels of technical or programming skills, while others rely heavily on social skills, or require a balance of both. Some of these skills, depending on their nature, are relatively easier to be transferred from other countries by immigrant workers, therefore making occupations heterogeneous in how effectively their corresponding tasks can be undertaken by these workers. The compatibility of immigrant skill can therefore be viewed as an occupation characteristic that commands the intensity of competition between the immigrant and native workers for positions in each occupation. To set the idea, consider two occupations that are very distinct in terms of the set of the skill requirements they entail, namely "lawyer" and "engineer". While the former occupation entails extensive interaction with clients, social perceptiveness and persuasion, the latter relies mostly on technical knowledge that would help with developing mathematical models and computational methods. Note that both jobs are considered high-skill occupations. However, the set of skills required for the two jobs are quite different. To the extent that natives have comparative advantage in conducting social skill-intensive tasks relative to their non-native counterparts, the degree of labor market competition between natives and immigrants would be relatively lower for the lawyer occupation as compared to the engineer occupation.

The skill requirements for an occupation and the extent to which they are compatible with those possessed by immigrants are not directly observable. I overcome this problem by proposing an objective empirical measure of immigrant skill compatibility based on the observed relative labor market participation of immigrant workers across different occupations. To this end, I exploit a comprehensive dataset of H-1B petitions filed by U.S. employers for positions in different occupations, combined with the data on the distribution of workers across occupations and industries from the Occupational Employment Statistics (OES) dataset. Based on this measure, I construct the key variable of my analysis, the share of the industry's total labor costs associated with immigrant skill compatible occupations. This variable, termed Compatible Labor Share (CLSHARE), is high for industries in which skilled immigrants and natives compete for a larger share of labor expenses.

I show that the CLSHARE robustly and positively predicts future returns in the cross-section of the U.S. stocks. In particular, firms in the high-CLSHARE quintile generate 8.78% higher annual abnormal stock returns compared to those in the low-CLSHARE quintile. These results are robust to adjusting returns for financial leverage as well as to variations in the sample selection, portfolio formation, and the way the measure is constructed. I also confirm the robustness of these results by running Fama and MacBeth (1973) regressions of stock returns on lagged values of CLSHARE and other firm characteristics to ensure that the observed return spread is not driven by other firm attributes that are known in the literature to predict returns. In addition to the conventional firm-level accounting variables, I also include occupation characteristics-based variables that have been recently shown to have predictive power for the cross-section of stock returns (Zhang (2017); Sharifkhani (2018)).

Motivated by the search and matching framework pioneered by Diamond-Mortensen-Pissarides, I propose a mechanism that explains the observed relation between CLshare and the cross-section of expected equity returns. As argued before, CLshare proxies for firms' ability to source their desired labor in the international skilled labor market through immigration. Importantly, the additional supply of skilled labor available through this channel is subject to variations induced by exogenous immigration policy shocks. Therefore, a shock that restricts access to skilled immigrants would disproportionately reduce the supply of labor in occupations for which skilled immigrants are most compatible, leading to an increase in the labor market tightness associated with these occupations. In a setting where wages are determined through a Nash bargain between workers and the firm, a tighter market translates into higher wages through a reduction in the firms' outside option (Elsby and Michaels (2013)). This implies that shocks that limit firms' access to skilled immigrant workers are expected to give rise to higher wages for the subset of jobs in which these workers are the desired candidates. This is what I find empirically. I exploit a natural experiment based on the reduction in the legislative cap for the H-1B visa program in 2003 to establish a causal link between the supply of immigrant skilled labor and the wages associated with occupations that can be effectively undertaken by these workers. Specifically, in a difference-in-differences estimation framework, I show that as the result of this restrictive policy, occupations in which immigrants had the most compatible skills experienced a disproportionate increase in their wages relative to otherwise similar occupations. Moreover, I show that this increase in the occupational wage gap translates into a higher increase in the labor expenditure for high-CLshare firms relative to their low-CLshare peers.

This finding is consistent with the idea that restrictive immigration policy shocks have a larger adverse effect on the labor expense of the high-CLshare firms, thus making their cash flows counter-cyclical with respect to these shocks. From a general equilibrium perspective, restrictive immigration policy shocks can adversely affect firms' productivity by increasing their search and training costs, leading to states with lower aggregate consumption and higher investor marginal utility. This, in turn, renders firms with greater CLshare as riskier. I find evidence consistent with this general equilibrium view: the risk associated with restrictive immigration policy shocks, when estimated based on the Generalized Method of Moments (GMM) using a host of proxies for these shocks, is in fact negatively priced in the market.

The proposed mechanism hinges on the fact that reductions in the supply of skilled immigrants have an asymmetric effect on the firms' cash flows through wages. In this case, the observed return spread should be less pronounced among firms in industries where wages are inherently less likely to change in response to these shocks. Consistent with this prediction, I find that the positive relation between CLshare and future stock returns is significantly weaker among industries in which the wages are inherently more rigid, as measured by their extent of labor unionization (Holden (1994); Goette, Sunde, and Bauer (2007); Holden and Wulfsberg (2008)). Next, I show that the level of training required for the job is an important determinant of the relation between CLshare and the expected returns. Specifically, I show that the positive relationship between CLshare and expected returns is concentrated among firms with the highest share of skilled labor, in line with this subset of firms finding it more difficult to offset the effect of restrictive immigration policy shocks by simply training native workers. Finally, motivated by the findings in the literature highlighting the importance of social skills as a factor that gives native workers a competitive advantage over their immigrant counterparts, I show that the positive CLshare-return relation is in fact weaker among industries that heavily rely on occupations that have strong social skills as their requirements.[2] This is consistent with immigration policy shocks being an unlikely source of significant variations in the supply of workers with the type of skill that is required by firms in these industries. Altogether, these findings support the hypothesis that the risk premium is dictated by the heterogeneity in the firms' exposure to variations in the supply of immigrant skilled workers through the labor costs channel.

I rule out several alternative mechanisms that could explain the return spread. In particular, I examine whether the premium could be attributed to a positive, rather than a negative, joint reaction of the firms' performance and household consumption to restrictive immigration policy shocks. Based on a host of empirical tests, including an event study on the "Buy American, Hire

[2]See for instance Lewis (2011), Hunt (2015), and Gentili and Mazzonna (2017) for evidence on the role of language in determining the degree of substitutability between foreign and native workers.

American" executive order, I rule out this hypothesis as an explanation for the observed return gap. I also show that the results are unlikely to be driven by heterogeneous labor demand across industries.

The empirical findings presented in this paper contribute to a growing literature that links firms' labor force heterogeneity and the cross-section of stock returns.[3] Donangelo (2014) proposes labor mobility as a proxy for the flexibility of workers to move away from firms in an industry during bad times, and shows that firms in more mobile industries are more exposed to aggregate shocks. Zhang (2017) studies firms' option to replace routine-task labor with machines as the firm-level characteristic that induces variations in cross-section of expected returns. In this framework, the option to automate jobs enables firms to reduce their exposure to systematic risk by increasing their efficiency during bad times. In this paper, I introduce a new source of labor force heterogeneity across firms that generates meaningful variations in the cross-section of expected equity returns: the ability to take advantage of foreign labor market through immigration programs.

This paper also contributes to the literature on the domestic welfare effects of immigration. The primary focus of many of these studies is on the distributional effects of immigration policies on local income (Blau and Kahn (2015); Ozden and Wagner (2014)) and employment (Cadena, Duncan, and Trejo (2015)). Clemens (2017) identifies the employment effect of shocks to the supply of immigrant labor within farm jobs. In my analysis, I also focus on a specific category of occupations, namely those identified as being suitably fit for skilled immigrants, and show that negative supply shocks have a positive effect on the wages of the treated occupations. A number of recent studies have investigated the importance of the supply of skilled immigrant labor on firms' performance. Xu (2017), for instance, identifies a reduction in the investment rate for the firms that are most dependent on workers hired through the H-1B program as the result of an exogenous reduction of the supply of H-1B workers. Ashraf and Ray (2017), on the other hand, find that these H-1B dependent firms significantly reduce their R&D investments in response to these shocks, leading to a significant decline in their patents and an increase in their SG&A expenditure. While the focus of these studies on the corporate finance implications of immigration policy provides valuable insight into how these policies are factored in firms' corporate decisions, the asset pricing implications of these policies are still largely unexplored in the finance literature. This paper is the first to fill this

[3]See for instance Eisfeldt and Papanikolou (2013), Kuehn, Simutin, and Wang (2017), Belo, Lin, and Bazdresch (2014), Belo, Li, Lin, and Zhao (2017), Kilic (2017).

gap by showing that these policies are an important source of risk in financial asset markets.

1 Data

In this section, I introduce the data and describe how I construct the occupation-level Immigrant Skill Compatibility measure as well as the proxy for the firms' ability to acquire workers from the foreign labor market through immigration, which is the key variable in my empirical tests. I then report the characteristics of occupations and firms that are differentiated based on these measures.

1.1 Accounting Data and Asset Prices

My sample includes common stocks (share code of 10 or 11) listed on Nasdaq, NYSE and AMEX (exchange code of 1, 2 or 3) available on Center for Research in Securities Prices (CRSP). Following the literature, I exclude micro-cap firms, defined as those within the lowest 5% of the cross-sectional distribution of market capitalization in each year, to avoid anomalies driven by the small-size firms (Fama and French (2008)). I use accounting data from Compustat Fundamentals Annual to construct variables that represent various firm characteristics used in the tests. In the Appendix, I provide a more detailed description of the data and the accounting variables used in my empirical tests.

1.2 Constructing the Measures

The key empirical variable in my analysis is the CLshare, which measures the extent to which a firm can benefit from access to foreign skilled labor markets through immigration. As a first step to construct this measure, I introduce an occupation-level proxy for how effectively foreign workers can conduct the tasks associated with an occupation compared to native workers. The proposed measure builds on the intuition that the relative fitness of skilled immigrants for an occupation can be inferred from the demand for this type of labor in that occupation relative to other occupations. Specifically, for two occupations that have equal access to immigrant labor, immigrant workers would be in more demand in the occupations where their productivity is comparable with that of their local peers, making skilled immigrants close substitutes for native workers in these type of occupations.

1.2.1 Data and Methodology

The measure for the relative demand for skilled foreign workers proposed in this paper is based on the number of petitions filed for H-1B visas by the U.S. employers for each occupation in the economy. This visa program, governed by the Immigration Act of 1990, allows U.S. employers to hire foreign aliens on a temporary basis for a certain set of occupations, known as the "specialty occupations".[4] Unlike most other non-immigrant visas, the petition for H-1B visa is submitted by the sponsoring U.S. employers to the U.S. Citizenship and Immigration Services (USCIS) upon receiving the required initial approvals from the Department of Labor. The number of foreign nationals who may be permitted to obtain and work under the H-1B status is subject to a limit known as the "H-1B cap". Importantly, this cap has been subject to changes a number of times since the inception of this visa program in 1990. Specifically, the cap was set at 90,000 until 1998, which was then increased to 115,000 in 1999 and 2000, followed by another increase to 195,000 for the years 2001 until 2003, when it was reverted back to 65,000 for the 2004 fiscal year. Currently, the maximum number of petitions approved for initial employment under this visa category is 65,000, with an additional 20,000 for those with master's or higher degrees from the U.S. universities.

I use a comprehensive set of data extracted from all H-1B petitions filed by U.S. employers from 1997 to 2016, both for initial employment as well as continuing employment. The data, which is obtained through a Freedom of Information Act (FOIA) request filed with USCIS, contains information about the sponsoring employer, the requested start date for the visa, the category of the offered job and the offered compensation, as well as information about the prospective H-1B employee, including the education level and the country of origin. Occupations in the data are classified by their 3-digit Dictionary of Occupational Titles (DOT) codes. I consider the starting year of the requested visa as the year in which the immigrant worker is needed by the employer to take on the job position. Therefore, I measure the demand for immigrant skilled workers in each occupation-year by counting the number of petitions with the corresponding occupation code and starting year.

[4] As per the U.S. Citizenship and Immigration Services, for a job to qualify as a specialty occupation, "(a) Bachelor's or higher degree or its equivalent is normally the minimum entry requirement for the position, (b) The degree requirement for the job is common to the industry or the job is so complex or unique that it can be performed only by an individual with a degree, (c) The employer normally requires a degree or its equivalent for the position, (d) The nature of the specific duties is so specialized and complex that the knowledge required to perform the duties is usually associated with the attainment of a bachelor's or higher degree."

It is important to note that the differences in the demand for foreign labor across occupations can be driven by different sizes of labor force associated with each occupation. To address this problem, I normalize the observed demand for skilled immigrant labor in each occupation by the total number of employees in that occupation at the national-level from the Bureau of Labor Statistics Occupational Employment Statistics (OES) dataset. The data provides employment in every occupation in each industry using surveys covering a stratified sample of 200,000 establishments every six months over three-year cycles from 1988 to 2016. Each industry is surveyed every year during my period of study, resulting in the coverage of roughly 62% of total U.S. employment. To find the employment for each occupation at the national level, I aggregate employment by occupation across industries in each year.[5] Using the resulting matched dataset of national occupational employment and the H-1B petitions, I then construct the Immigrant Skill Compatibility (ISC) index for occupation j in year t ($ISC_{j,t}$) as the ratio of the total number of H-1B petitions in occupation j with a proposed starting year t, divided by the total number of employees in that occupation-year.[6]

The final step in constructing CLshare is to find the fraction of each industry's labor costs that is associated with the high-ISC occupations, i.e., those in which immigrants are a relatively better fit. Following a similar approach as Zhang (2017), I identify a job as being high-ISC in year t if it falls in the top quartile of all occupations in terms of the ISC index in that year. I find

[5] Another potential concern with the occupation-level measure of immigrant skill compatibility, the way it is defined, is that the cross-occupation variations in the demand for the skilled immigrant labor could partially be induced by the heterogeneity in the industry growth rate, for instance due to sectoral reallocation shocks, which can potentially result in greater demand for labor in a subset of occupations compared to others. I will address this concern in Section 4 using a direct measure for labor demand, and show that the results are unlikely to be driven by the heterogeneity in labor demand across industries.

[6] For the years prior to 1999, the BLS uses its own five-digit OES taxonomy to identify occupations in its OES data. In 1999, it switched to the six-digit 1999 OES taxonomy, and then to the 2000 SOC taxonomy for year between 2000 and 2009. Since 2010, occupations in the OES dataset are identified by their 2010 SOC taxonomy. To find the compatibility measure for each occupation in the OES data, I cross-walk the DOT codes in the H-1B petitions dataset to their corresponding occupations in the OES dataset using concordance tables provided by the BLS and the Analyst Resource Center. The concordance table from DOT to OES taxonomy is available at http://data.widcenter.org/download/xwalks/. Also, the concordance table from DOT to 2010 SOC is obtained from the Department of Education website, available at https://www2.ed.gov/rschstat/eval/rehab/support/doc-soc.xls. Finally, the 2000 SOC to 2010 SOC is available from the BLS website at https://www.bls.gov/soc/soccrosswalks.htm. In general, occupations in the OES data are defined based on a more granular classification than those in the H-1B data. This leads to cases where occupations in H-1B dataset are mapped to more than one occupation in the OES dataset. I reconcile these overlaps by dividing the H-1B employment in each occupation among its mapped OES occupations in proportion to their total level of employment. As an alternative method, I reconcile the overlap by dividing the number of H-1B employees in each DOT-coded occupation between its mapped OES occupations proportional to their overlaps in the constructed cross-walk. I find that the results remain qualitatively unchanged.

the corresponding employment and wages for each occupation-industry-year from the OES dataset, where industries are classified based on three-digit SIC classification for years prior to 2002 and four-digit NAICS classification afterwards. I then define $\text{CL}\textsc{share}_{i,t}$ for industry i in year t as

$$\text{CL}\textsc{share}_{i,t} = \sum_j \mathbb{1}[ISC_{j,t} > ISC_t^{P75}] \frac{emp_{j,i,t} \times wage_{j,i,t}}{\sum_j emp_{j,i,t} \times wage_{j,i,t}}, \tag{1}$$

where $emp_{j,i,t}$ and $wage_{j,i,t}$ are the employment and wage for occupation j in industry i in year t, making the product of the two terms being equal to the total labor expenditure associated with that occupation-industry-year.[7] To maintain consistency, throughout this study I adopt a similar approach when constructing proxies for the intensity of other job characteristics, such as the skill, offshorability, information content and social skills. A detailed description of these job characteristics and the measurement methodology is provided in the Appendix.

Note that considering that the main focus of my analysis in this paper is on the cross-sectional variations in the demand for foreign skilled labor across occupations, regulatory changes in the H-1B cap over time are expected not to affect the validity of this measure to the extent that occupations are not differentially treated by these changes.

1.3 Inspecting the Measures

I begin my examination of the occupation-level ISC measure by inspecting a list of jobs that are identified as those in which immigrants are most competitive as implied by this measure. Table 1 lists a set of occupations with the highest average ISC from 1997 to 2016. Most of these occupations seem to involve a relatively low level of routine task, and require a high level of skill. Moreover most of these high-ISC jobs involve processing and documenting information, but not necessarily a high level of social interactions. I find that many of the jobs in the dataset show up as having a ISC level equal to zero. This is not surprising, considering that some jobs do not qualify for H-1B visa based on the requirements set forth by USCIS, or that no H-1B petitions have been filed for those jobs during the period of study.

[Table 1 about here]

[7] As will be shown in future sections, the main results in the paper are robust to using alternative thresholds for defining the high-ISC jobs, using employment level rather than labor costs, or using the levels of ISC index rather than the indicator variable in construction of this measure.

Considering that the regulations that shape the demand for H-1B workers can be potentially biased towards certain job characteristics, a potential concern with the ISC measure is that it might capture other job characteristics, such as the required level of training or the routineness of the job, that would affect asset prices through other channels. For instance, a job with lower skill requirements would be inherently less costly for the firm to eliminate in response to specific shocks, offering a channel through which the skill can affect asset returns (Belo et al. (2017)). Also, as suggested by Zhang (2017), firms with a larger share of routine-task labor would have the option to replace a larger proportion of their workers with machines in bad times, implying that such firms can operate as a hedge against aggregate consumption shocks. Therefore, it is important to formally examine the relation between the key job characteristic used in this paper, namely the ISC, and other job characteristics that can potentially induce variations in asset prices. Panel A of Table 2 presents the correlation between ISC and an important set of job characteristics, namely the level of training required for the job, social interaction requirement, routineness, offshorability, and the intensity of information content. While none of these alternative job characteristics seem to be abnormally correlated with ISC, the general direction of the correlation as implied by their signs are in line with the intuition. Specifically, ISC is found to be positively correlated with training, and negatively correlated with routineness. Moreover, jobs with high levels of ISC seem to be easier to relocate abroad, and have high information content.

[Table 2 about here]

Panel B of Table 2 illustrates the percentage of H-1B petitions that were filed for positions in each major occupation group, and reports how jobs identified as those in which immigrants are close substitutes for native workers are distributed across occupation groups. While the majority of the H-1B petitions are for positions in professional and managerial occupations, the smallest portion of these visas are granted to occupations under services and agriculture occupational group. A similar pattern is observed when I examine the percentage of employees in each major occupation group that are working in positions identified as high ISC. Occupations in the services group seem to have the lowest percentage of jobs in which immigrants can compete, followed by those in clerical and sales.

The key empirical measure used in this study, CLshare, is the percentage of the industry labor expenditure that is associated with jobs for which immigrants have compatible skills. As a first step to examine the properties of this measure in relation to other characteristics, I provide in Table 3 a list of industries with the highest and lowest CLshare, namely those which are most and least likely to find skilled immigration programs an effective channel through which to hire workers. Industries with the lowest CLshare are typically the ones with the lowest concentration of occupations that qualify for H-1B. On the other hand, industries where the "specialty occupations" are most prevalent constitute the list of industries with the highest level of CLshare.

[Table 3 about here]

I proceed by examining which sectors do firms with the highest and lowest CLshare belong to. Panel A of Table 4 reports the average and the standard deviation of the CLshare for each sector from 1997 to 2016. Sectors with the highest CLshare, i.e. those with the highest concentration of occupations in which foreign workers can compete with native workers, are the services and the manufacturing sectors. On the other hand, retail, public administration and agriculture are among those where immigrant workers are least likely to be good replacement for their native counterparts. Overall, the results indicate that CLshare is well-dispersed across sectors, refuting the possibility that the cross-sectional variations in CLshare is concentrated in a particular sector. Moreover, the standard deviation of CLshare is also relatively large within sectors, implying that it can induce variations in expected returns within industries as well. In the next section, I show that this is in indeed the case.

How different are firms distinguished by their levels of CLshare in terms of other characteristics? Each year, I sort industries by their CLshare and form quintile portfolios of stocks based on the value of CLshare in their corresponding industry. Panel B of Table 4 presents the equally-weighted average characteristics and moments for each quintile portfolio. The average CLshare ranges from 0.109 in the bottom quintile to 0.626 in the top quintile, implying that there is substantial heterogeneity across industries in terms of this measure. While book-to-market ratios and profitability are decreasing with CLshare, the opposite applies to firms' innovative activities and investment as a fraction of property plants and equipment. Moreover, market leverage seems to be negatively related to CLshare, suggesting that firms with a smaller proportion of labor with which skilled immigrants can compete take on more leverage. In addition, firms with higher CLshare have a larger proportion of skilled and offshorable labor, and rely more heavily on information intensive occupations. A potential concern that arises from these findings is that the observed return spread could be driven by the difference in the concentration of routine-task labor or offshorable occupations across industries (Zhang (2017); Sharifkhani (2018)), or by the cost they face when trying to adjust their labor stock (Belo et al. (2014); Eiling, Kan, and Sharifkhani (2018)). To address this concern, I directly control for the concentration of routine-task, offshorable, and high-skill occupations in the industry in my asset pricing tests. Finally, CLshare is found to be almost uncorrelated with the direct measures of labor demand, namely the jobs openings rate and the layoffs rate. This is consistent with the relative demand for foreign labor, as measured by CLshare, being driven by the extent to which immigrant workers can effectively undertake tasks in an industry, above and beyond the general demand for labor in that industry. I also find that firms in the highest CLshare quintile have, on average, annual returns that are around 4.5% higher over the next year compared to those in the low-CLshare portfolio.

Next, I examine how persistent the CLshare is as an industry characteristic. To this end, I calculate the average frequency with which an industry transitions from one CLshare quintile to another over a one year period. I present this analysis in Panel C of Table 4. For industries in the top quintile of the distribution of CLshare, the likelihood of transitioning to a lower quintile is smaller than 16%, suggesting that CLshare is a persistent industry characteristic.

[Table 4 about here]

2 Immigrant Skill Compatibility and Equity Returns

2.1 Portfolio Sorts

Each year t, I rank industries by the value of their CLshare in that year into quintiles and assign them to high-, mid- and low-CLshare portfolios, where the mid-CLshare portfolio is formed by pooling stocks in the second, third and the fourth quintiles. I then construct monthly time series of the stock returns for firms that belong to each portfolio starting in July of year $t+1$ while holding the portfolio for a period of one year, and calculate the equally-weighted and value-weighted average monthly return of each portfolio. To address the potential concern that the premium is a reflection of the differential exposure of the firms in these industries to risk factors irrespective of their actual exposure to changes in immigration policy, I estimate abnormal excess returns with respect to the five factor model of Fama and French (2015). Table 5 summarizes the abnormal returns for each portfolio and for the portfolio that is long the quintile with the highest CLshare and short the quintile with the lowest CLshare. I also present the loadings associated with the five risk factors in the model, namely, market (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA).

The risk-adjusted returns of the CLshare-sorted portfolios indicate a positive relation between CLshare and future stock performance. As reported in Panel A of Table 5, firms in the high-CLshare quintile earn the highest annual average abnormal return of 7.84% , while those in the low-CLshare quintile generate average abnormal return of -0.95%, yielding an annual abnormal return spread of 8.78%, with a t-statistic equal to 3.40. I also examine if my results are robust to adjusting returns for the leverage taken by the firm. This is especially important considering that part of the search and training costs associated with hiring labor can potentially be financed through debt. Therefore, firms with a relatively limited ability to take advantage of immigrant skilled labor could be more levered, as they face higher search and training costs resulting from their limited hiring options. This implies that the observed positive return spread could be explained by an endogenous negative relation between CLshare and leverage. I rule out this possibility by testing the robustness of my results using returns that are adjusted for leverage, following the method proposed by Donangelo (2014). Specifically, I construct the unlevered stock returns as

$$r_{i,y,m}^{Unlevered} = rf_{y,m} + (r_{i,y,m} - rf_{y,m})(1 - MktLev_{t,y-1}) \tag{2}$$

where $r_{i,y,m}^{Unlevered}$ is the return of firm i in month m of year y adjusted for the leverage, $rf_{y,m}$ is the monthly risk free rate in the same period, and $MktLev_{i,y-1}$ is the market leverage for the firm at the end of year $y-1$. The results based on unlevered returns are essentially unchanged compared to those based on the raw returns. The unlevered high-minus-low CLshare portfolio generates an alpha that is equal to 8.35 with a t-statistics equal to 3.83.

[Table 5 about here]

Importantly, as shown in Panel B of Table 5, for value-weighted portfolio returns, the long-short alpha is still statistically significant at 5.08% annually, with a t-statistic that equals 2.0. This highlights the fact that immigration policies matter for investors' wealth. Similar to the results in Panel A, I find that adjusting the returns for leverage does not lead to a significant decline in the alpha obtained in the case with raw return, altogether suggesting that the possibility for the firm to hire from pool of skilled immigrants is an important predictor for future equity returns.

2.2 Fama-MacBeth Regressions

The results in the previous section support the existence of a strong positive relation between CLshare and future returns above and beyond what could be explained by the firms' exposure to standard risk factors. In this section, I take one step further and account for other firm characteristics that have been shown to have predictive power for the cross-section of expected stock returns. Specifically, I examine if the ability of CLshare to predict stock returns is subsumed by other firm characteristics. To this end, I perform monthly Fama and MacBeth (1973) regression of the form

$$R^e_{i,t+1} = \beta^0_t + \beta^1_t \cdot \text{CLshare}_{i,t} + \sum_{k=1}^{K} \beta^j_t \cdot X^k_{i,t} + \eta_{i,t}, \quad i = 1, \cdots, N_t \tag{3}$$

where $R^e_{i,t+1}$ is the excess return of stock i in month $t+1$, and $\text{CLshare}_{i,t}$ and $X^k_{i,t}$ are the value of the CLshare and the k-th control variable at the end of the most recent year. As control variables, I include the commonly used variables, log book-to-market (BM), log market value (Size), and the conditional beta with respect to the market (β^M). I also include a number of other characteristics recently found to explain expected returns. Specifically, I include the profitability (Prof) and free cash flow (FCF) from Novy-Marx (2013), market leverage (MktLev) and operating leverage (OpLev) from Zhang (2017), and hiring rate (HN) from Belo et al. (2017). I also control for the exposure to economic policy uncertainty shocks (β^{EPU}) introduced by Baker, Bloom, and Davis (2016), in light of the evidence presented by Brogaard and Detzel (2015) who show that policy uncertainty is a priced factor for equities. Finally, to mitigate the concern that variations in expected returns is induced by other occupational properties that correlate with ISC, I include a number of occupation-based firm characteristics that are shown to induce cross-sectional variations. To this end, I include the share of routine-task labor from Zhang (2017) and the share of offshorable labor from Sharifkhani (2018) for the firm's corresponding industry, both defined following Acemoglu and Autor (2011). I windsorize all independent variables cross-sectionally at the 1% and 99% levels.

The summary of the results from the Fama-MacBeth regressions are reported in Table 6. Throughout all specifications, the coefficient associated with CLshare is positive and significant. The magnitude of the coefficient implies that one standard deviation increase in CLshare (0.168) is associated with an increase in the annual excess return of roughly 2.8%. Shifting from the bottom CLshare quintile to the top CLshare quintile is equivalent to an increase of about 3.08 standard deviation in CLshare, suggesting an annual return spread of 8.62% in the two portfolios, consistent with the results presented in Table 5.

[Table 6 about here]

3 Identification of the Channel

The reported results confirm that CLshare has an economically and statistically significant predictive power for the cross-section of future equity returns. Importantly, this predictive power is not explained by the correlation between CLshare and other predictive variables that have been identified in the literature, or by firm's exposure to other risk factors. In this section, I investigate the underlying channel through which CLshare induces variations in the cross-section of expected stock returns. I first provide evidence showing that different occupations, depending on the extent to which immigrants have skills that are compatible with their required set of skills, have differential wage exposures to immigration policy shocks. Next, I show that this occupation-level exposure translates into a differential labor-cost exposure across firms, especially among industries where wages are inherently less rigid. Finally, using a variety of tests, I provide further evidence that the effect of immigration policy shocks on firms' labor market tightness and labor expenditure is what most likely underlies the observed risk premium.

3.1 Access to Skilled Immigrants and Wages: Evidence from the 2003 H-1B Cap Drop

The additional supply of skilled labor through immigration is subject to variations induced by exogenous factors such as the immigration policy shocks. As the result of these shocks, different occupations, depending on the extent to which their required skills are compatible with the skills possess by immigrant workers, would experience differential changes in their effective labor supply, and therefore labor market tightness. This induces variations in the growth rate of wages across occupations in an environment where wages are determined in a Nash bargain between the workers and the firm (Diamond (1982); Mortensen and Pissarides (1994)). Specifically, shocks that limit firms' access to skilled immigrant workers are expected to lead to higher wages associated with jobs in which these workers are most competent. I show that this is indeed the case by exploiting a natural experiment, in a difference-in-difference framework, based on the 2003 reduction in the legislative cap for the H-1B visa program.

In October 2003, the U.S. Congress reduced the per-annum cap for newly issued H-1B visas from 195,000 to 65,000 for fiscal year 2004 and beyond. In the years immediately preceding the policy change, the H-1B visa cap was not binding.[8] For instance, in 2003, the number of H-1B petitions of new visa issuances were 105,314 which is remarkably below the 195,000 limit that applied to the H-1B petitions in that year. The cap became binding, however, in 2004, as 130,497 petitions were being considered for only 65,000 visas. As a result, legal employment became more difficult to secure for firms that relied on this type of workers.

As a result of this policy change, occupations in which skilled immigrants were a good fit experienced a relative increase in their wages compared to other occupations with otherwise similar characteristics. To show this, I employ a difference-in-differences (DD) estimation in which the 2003 H-1B cap drop is considered the treatment event, and the intensity of treatment is the 2002 value of the Immigrant Skill Compatibility (ISC) index of the occupations, which proxies for the extent to which the tasks associated with an occupation can be effectively undertaken by a skilled immigrant.

Prior to conducting the difference-in-difference analysis, it is important to test if the parallel trends assumption holds in the lead up to the 2003 H-1B cap drop. It specifically helps us rule out the potential effect of the confounding factors that can bias the estimates of the causal effect of the shock by inducing correlation between ISC and trends in wage growth in the pre-treatment period. To this end, I estimate the following OLS regression

$$wage_{jit} = \gamma_j + \lambda_t + \sum_{2000<k<2004} \beta_k \cdot ISC_j \cdot \tau_{t,k} + \beta \cdot ISC_j \cdot Post_t + \delta' \cdot X_j \cdot Post_t + \epsilon_{jt}, \quad (4)$$

[8] Xu (2017) provides a detailed timeline for the changes in the H-1B cap over a window surrounding this policy shock.

where $wage_{jit}$ is the log annual average wage associated with occupation j in industry i in year t, ISC_j is a dummy variable that takes on a value of 1 if the Immigrant Skill Compatibility index for occupation j is in the top 25% of all occupations at the end of year 2002, and zero otherwise. $\tau_{t,k}$ denotes a dummy variable that takes on the value of 1 if $t = k$, and zero otherwise. Similarly, $Post_t$ is a dummy variable that takes on a value of 1 if year t is in the post-treatment period, namely 2004 and onward. I limit the sample period to 2000-2007, therefore making the year 2000 the baseline period for the comparison of the wage-gap between the treatment and control occupation groups. In addition to specifications with year fixed effect, I test if the results are robust to controlling for the cross-industry variations in wages by including the industry-year fixed effect in the above specification. I also include X_j, which is the set of occupation-level control variables, namely Skill, Routineness, Offshorability, and Social Skill Intensity, all represented as a dummy variable that takes on a value of 1 if the occupation is among the top quartile of all occupations in terms of the corresponding job characteristics, and zero otherwise. Controlling for these alternative occupational characteristics is important, considering the potential confounding effects from other job characteristics that could offset an otherwise existing trend gap between the two occupation groups. As an alternative way to control for the variations in the other job characteristics across occupations, I define the characteristics-adjusted wage as the component whose variations are not explained by these other job characteristics. This procedure would therefore eliminate the differences across wages that are induced by these other occupational characteristics. To this end, I run the following regression:

$$wage_{jit} = c + \lambda_{it} + \delta \cdot \tilde{X}_j + \epsilon_{jit} \tag{5}$$

where $wage_{jit}$ is the average annual wage for occupation j in industry i in year t, and $\tilde{X}_j$ are the occupation characteristics for which I adjust wages, namely, Skill, Routineness, Social Skill Intensity and Offshorability, as represented by their continuous values. My variable of interest, the characteristics-adjusted wage, is therefore simply the residual ϵ_{jit} from this regression. By replacing $wage_{jit}$ with ϵ_{jit} in equation (4), I can therefore estimate the differential effect of the policy on the treated jobs above and beyond what could be explained by other job characteristics.

The results are reported in Table 7. Throughout all specifications, the coefficient associated with the treatment occupations group during the post-treatment period is positive and significant, while the pre-treatment period interaction terms are typically statistically insignificant from zero, meaning that the wage differentials are not significantly different from those in the baseline year.

[Table 7 about here]

Turning to the main difference-in-differences analysis, I estimate the results from the following regression:

$$wage_{jit} = \gamma_j + \lambda_t + \beta \cdot ISC_j \cdot Post_t + \delta \cdot X_j \cdot Post_t + \epsilon_{jt} \tag{6}$$

Similar to equation (4), $Post_t$ represents a dummy variable for the post-treatment period, which takes on a value of 1 if year t is in the post-treatment period, namely 2004-2016. The coefficient of interest, β, should be positive if the policy shock has differentially increased the wages associated with the high-ICS occupations. As reported in Table 8, this coefficient is positive and significant. This suggests that occupations in which immigrant workers were relatively more competitive experienced a significantly larger increase in their wages compared to occupations in which this type of labor is an imperfect substitute for native workers. Specifically, the results indicate that the high-ICS occupations experienced an average increase of as much as 6% in their wages as a result of this restrictive immigration policy shock. I further test if the effect also holds across occupations that belong to the same industry. This is to mitigate the concern that the results are driven by industry-level shocks that can affect wages at the industry level. Therefore, as an alternative specification, I replace the time fixed effect λ_t with the industry-year fixed effect λ_{it}. The results, reported in columns (3) and (4), suggest that the effect holds after controlling for potential variations in industry-level wages. Furthermore, I investigate if the results are driven by the wage differentials across industries for the same occupation by including industry-occupation fixed effect in the above equation. As shown in columns (5) and (6), the coefficient associated with the interaction term remains significant even after controlling for the industry-occupation fixed effect, in line with the notion that the shock leads to an increase in the wages associated with an occupation in the same industry over time.

[Table 8 about here]

These results suggest that in response to this restrictive immigration policy, occupations in which immigrant workers were better fit experienced a relative increase in their wages compared to otherwise similar occupations, where this increase in the wage gap is not explained by other job attributes and industry-level variations in wages.

Next, I investigate if the observed relative increase in the wages associated with the high-ISC occupations translates into a relative increase in the average wages and labor expenditure for industries that rely most on workers employed in this type of occupations, namely high-CLshare firms. This is particularly important, considering that firms can offset the cash flow effect of an increase in wages of its high-ISC occupations by reducing the wages associated with low-ISC occupations, or by reducing their stock of workers in high-ISC occupations, therefore keeping their total labor expenditure unchanged. To this end, I repeat the above difference-in-differences framework, this time defining as the treatment group the industries with CLshare in the upper quintile across all industries at the end of 2002. In addition, I investigate if the effect of this shock depends upon the inherent rigidity of wages in the industry. Motivated by the findings of Holden (1994), Holden (2003), Dustmann and Schonberg (2009) who established a positive relation between labor unionization and wage rigidity, I use labor unionization as a proxy for the extent of the wage rigidity in each industry. Specifically, I define a dummy variable $Union_{i,t}$ which takes the value of 1 if the industry to which the firm belongs is in the top quintile of all industries in terms of labor unionization, defined as the percentage of workers in the industry that are union members, and zero otherwise. I estimate the differential effect of the shock on labor expenditure across industries with high and low wage rigidity using the following difference-in-difference-in-differences (DDD) specification:

$$\begin{aligned}
Exp_{it} = {} & \gamma_i + \lambda_t + \beta \cdot \text{CL}\textsc{share}_i \cdot Post_t + \delta_1 \cdot Union_{i,t} + \delta_2 \cdot Union_{i,t} \cdot Post_t \\
& + \delta_3 \cdot \text{CL}\textsc{share}_i \cdot Union_{i,t} + \delta_4 \cdot \text{CL}\textsc{share}_i \cdot Union_{i,t} \cdot Post_t \\
& + \delta_5 \cdot X_{i,t} \cdot Post_t + \epsilon_{it}
\end{aligned}$$

I use three sets of proxies for labor expenditure (Exp_{it}): W_{it}^{m}, which is the hourly median wage in the corresponding industry, W_{it}^{emp} which is the employment-weighted average of the hourly wages across all occupations in the industry, and LC_{it} which is the total labor costs for the industry, defined as the product of the employment and the associated wage in each occupation in industry i, aggregated across occupations in that industry.

The results are reported in Table 9. From columns (1), (3) and (5), we can infer that the restrictive immigration policy shock in 2003 led to an increase in the labor expenditure for firms in industries with high CLshare, relative to those that belong to the low-CLshare industries. Moreover, the results from the DDD analysis indicate a pronounced difference in how much the gap between the labor costs of high- and low-CLshare firms increase depending on the degree of wage rigidity. In particular, the relative increase in the labor costs associated with firms in the high-CLshare industries is significantly smaller when wages are inherently more rigid, implying that firms in this subset of industries are less likely to be affected by the shocks to immigration policy than those in industries where wages are less rigid. In other words, the effect of immigration policy shocks is most pronounced in the subset of industries in which wages are intrinsically less sticky. In the following section, I investigate if this finding can be linked to the identified asset pricing findings in the context of my proposed hypothesis.

[Table 9 about here]

3.2 Risk Premium and the Role of Wages

Based on my hypothesis, shocks that limit firms' access to skilled immigrant labor force impose upward pressure on the wages associated with high-ISC occupations. This is the case when wages are determined in a Nash bargain between workers and the firm, which entails that a negative shock to the supply of immigrant labor leads to a decrease in the value of the outside option for the firm, which in turn increases the share of the surplus gained by workers in these occupations. In other words, shocks that reduce the likelihood of finding a matched employee in certain positions for firms result in relatively higher wage growth for the subset of workers that are employed in those positions. As illustrated before, the resulting upward pressure on the wages of this subset of workers, in turn, induces a negative pressure on the cash flow of firms that rely most on these occupations.

If these variations in the wages are what drives the observed risk premium associated with immigration policy shocks, one would expect that investors would require a smaller premium to hold equity in industries where wages are inherently more rigid. I test this conjecture by running a panel regression with month fixed effect using the monthly stock returns as the dependent variable, and the lagged values of CLshare, unionization and their interaction term as independent variables.

In alternative specifications, I also control for other firm characteristics introduced in Table 6, and include industry-year fixed effect to control for the unobserved time-varying heterogeneity across Fama-French 17 industries. The results are reported in Panel A of Table 10. Consistent with my proposed channel and the results in Table 9, I find that the interaction term between CLshare and the proxy for wage rigidity is negative and significant in all specifications, suggesting that the risk premium is in fact most pronounced among industries in which cash flow is more likely to be negatively affected by the negative labor supply shocks through wages.

[Table 10 about here]

3.3 Risk Premium and the Role of Skills

I hypothesize that the level of training required for positions in an industry is an important determinant of the relationship between CLshare and the expected returns for that industry. Firms in the high-CLshare industries would find it relatively more difficult to find their desired labor when their access to immigrant workers becomes limited due to restrictive immigration policy shocks. This effect is expected to be even stronger if the type of tasks that the industry relies on requires a high level of training. Otherwise, the firm can counteract the effect of its limited access to its desired immigrant workers by hiring and training native workers. This is what I find empirically: the positive relationship between CLshare and expected return is concentrated among firms in which high-skill labor constitutes a larger share of labor costs. I test this hypothesis by running a panel regression similar to the one in Panel A of Table 10, this time using the "Skill" as the independent variable that proxies for the costs associated with training a new hire. Similar to the previous test, I include Skill as a dummy variable that takes on value of 1 if the industry belongs to the upper quartile of all industries in terms of the skill intensity in that year, and zero otherwise. The results, illustrated in Panel B of Table 10, are in line with this prediction: the positive relationship between CLshare and expected returns is concentrated among industries with the highest share of skilled labor.

Finally, I provide further support for the role of skill compatibility as a determinant of the firms' exposure to immigration policy shocks using social skills as a job attribute in which native workers potentially have comparative advantage over foreign workers. This measure is motivated by the findings of Gentili and Mazzonna (2017) and Lewis (2011) who show that language skills are among the most important impediments against the substitutability of immigrant and native labor. Therefore, occupations in which social interaction is a crucial part of the job are likely those in which immigrant workers are not as productive. This implies that the risk premium is expected to be relatively smaller among firms that rely heavily on occupations that require high levels of social skills as the supply of their most productive type of labor is not affected by immigration policy shocks. My empirical findings, as reported in Panel B of Table 10, are in line with this prediction. Consistent with the hypothesis that skill compatibility is an important determinant of the sensitivity of wages to immigration policy shocks, I find that the identified positive CLshare-return relation is in fact weaker among industries that rely most on occupations that require strong social skills.

4 Further Discussion

4.1 The Market Price of Immigration Policy Shocks

The key assumption underlying the hypothesis advanced in this paper is that the permissive immigration policy shocks are associated with states where investors' marginal utility is lower, making them require a premium for holding assets with greater exposure to such immigration policy shocks. In other words, the price of the risk associated with immigration policy shocks is assumed to be positive. An important question is whether this is consistent with general equilibrium. On the one hand, the probability that vacant jobs are filled increases as a result of positive immigration policy shocks, thereby lowering the unit hiring costs for firms. This, in turn, makes job creation more attractive for firms, leading to lower aggregate consumption in short term as more resources are spent to hire workers. In the long run, however, consumption is expected to increase due to the increased labor as a production factor, which consequently leads to higher productivity. Therefore, whether the marginal utility is negatively or positively affected by permissive immigration policy shocks depends on the relative magnitudes of risk aversion and the intertemporal elasticity of substitution.

In this section, I estimate the price of risk associated with immigration policy shocks using the generalized method of moments (GMM) based on a parsimonious linear model for the stochastic discount factor. Specifically, I estimate the coefficient associated with immigration policy shocks with a SDF specified as

$$m = a - \gamma_m R_{MKT} - \gamma_I \Delta I, \tag{7}$$

where R_{MKT} is the market return and ΔI is a proxy for immigration policy shocks. Following the advice of Lewellen, Nagel, and Shanken (2010), I impose as moment restriction that the specified SDF should price the cross-section of Fama-French 30 industry portfolios. As a proxy for immigration policy shocks, I use the return to the immigrant-minus-resident (ImR) portfolio, defined as a portfolio that is long firms belonging to highest CLshare quintile, and short those in the lowest CLshare quintile. This is in line with permissive immigration policy shocks resulting in a relative reduction in labor expenditure, and hence a more positive return for high-CLshare firms compared to their low-CLshare peers.

As a benchmark proxy for immigration policy shocks, I use R^e_{ImR}, which is the risk adjusted return with respect to the Fama-French five factors of the ImR portfolio, constructed by sorting firms into quintiles using the entire cross-section of firms. A potential concern with this approach is that the utilized factor, which is constructed based on CLshare as an industry characteristic, makes it likely that industries exhibit factor structure with respect to this specific factor. To mitigate this concern, I make use of an alternative factor, $R^{e,IN}_{ImR}$, which is constructed by sorting firms into quintiles within their corresponding Fama-French 17 industries. This mitigates, to some extent, the concern that the empirical estimates of the factor exposures is biased by potential structural dependencies between the ImR and dispersion in industry returns.

Another concern with the way the above factor is constructed is that adjusting the return spread between high- and low-CLshare quintiles for the Fama-French risk factors introduces noise, which can in turn bias my GMM estimates of γ_I. As a robustness test, I use an alternative proxy for immigration policy shocks, R_{ImR}, which captures the spread between the raw returns, rather than the risk-adjusted returns, of the high- and low-CLshare portfolios, while I also include the Fama-French five factors in the specification of the SDF.

The GMM estimates of γ_m and γ_I are obtained using the identity matrix to weight moment restrictions, where R_{MKT} and ΔI are normalized to have a mean equal to zero and a standard deviation equal to one. Moreover, I estimate HAC t-statistics that are computed using adjusted errors based on the Newey-West procedure with three lags. The results are reported in Table 11.

Across specifications, the estimates of the price of risk associated with immigration policy shocks is positive and significant. Consistent with the assumption in my hypothesis, this implies that states in which immigration policies are more permissive are associated with states where the marginal utility is relatively lower. As a result, a higher exposure to immigration policy shocks is expected to be associated with higher expected return.

[Table 11 about here]

4.2 Robustness Tests

I now demonstrate the robustness of the relation between CLshare and future stock returns. I use stock returns directly adjusted for size, value, and momentum factors, consider modified definitions of CLshare, include micro-cap stocks, exclude financial stocks, and conduct the analysis within industries. Table 12 summarizes the results of the robustness tests.

I begin by constructing the returns adjusted for firm characteristics that are known to have predictive power for stock returns in cross-section. This is especially important, considering my observation that some of these variables covary with the CLshare. To this end, I follow the methodology introduced in Daniel, Grinblatt, Titman, and Wermers (1997) by subtracting from the returns for each stock the return of its corresponding benchmark portfolio constructed by a sequential triple-sort of all stocks into 125 value-weighted portfolios by size, book-to-market, and past stock performance. The results, shown in Panel B of Table 12, suggest that making this adjustments does not lead to a dramatic difference in the relative future performance of high- and low-CLshare stocks. For instance, the average abnormal return spread when using DGTW-adjusted returns is 7.95% annually, compared to the 8.78% that was obtained when using raw returns setting.

Next, I investigate if using the continuous value of the ISC, rather than an indicator variable, in construction of CLshare would produce a lower expected excess return spread. To this end, I redefine CLshare based on a modified version of equation (1) as follows:

$$\text{CL}\textsc{share}_{i,t} = \sum_j \frac{emp_{j,i,t} \times wage_{j,i,t} \times ISC_{j,t}}{\sum_j emp_{j,i,t} \times wage_{j,i,t}}. \tag{8}$$

The results, provided in Panel C of Table 12, suggest that this approach results in an even more dramatic difference between the abnormal return of high and low CLSHARE portfolios, achieving a spread of 8.94% per annum.

The benchmark CLSHARE is defined as the fraction of the firm's total labor expenditure associated with high-ISC occupations. Another potential concern with the way this measure is defined is that using labor expenditure, rather than labor stock, can magnify the role of a small number of jobs, such as executives, that enjoy extremely high levels of wages. Therefore, the cross-sectional variations in my measure and the resulting return spread can simply be induced by variations in firms' executive compensation. I rule out this possibility by constructing the CLSHARE using the labor stock, rather than labor costs, as the weights to calculate the average industry-level CLSHARE. In other words, I use the following alternative formula to construct CLSHARE:

$$\text{CLSHARE}_{i,t} = \sum_{j} \mathbb{1}[ISC_{j,t} > ISC_t^{P75}] \frac{emp_{j,i,t}}{\sum_j emp_{j,i,t}}. \tag{9}$$

The results, reported in Panel D of Table 12, show that this alternative measure produces spreads that are similar in magnitude to the baseline setting, i.e. 7.93%, suggesting that the results are unlikely to be driven by cross-sectional differences in firms' staff compensation.

Next, I explore the sensitivity of the results to the ISC threshold used to identify jobs as immigrant skill compatible. In the baseline setting, this threshold is arbitrarily set at the $75th$ percentile of all occupations sorted by ISC in the year in which CLSHARE is being calculated. Panel E of Table 12 shows that the results are not sensitive to this value. The difference in future returns of stocks with high and low CLSHARE remains virtually the same when the measure is constructed using $80th$ percentile as the threshold.[9]

In Panel F of Table 12, I evaluate the robustness of my results to including microcaps, which I define as stocks with market capitalization below the 5th NYSE percentile. Also, in Panel G of Table 12, I test if the results are robust to excluding stocks with market capitalization below the 20th NYSE percentile. In both cases, the results suggest that the spread is not driven by stocks in a specific extreme size class.

Also, as shown in Panel H of Table 12, excluding financial firms from the sample, as is done in some studies, does not result in a dramatic difference in the abnormal return spread between the high and low CLSHARE portfolios.

[9] In untabulated results, I find this to be the case when set the threshold at 66th and 90th percentile as well.

I next investigate if the observed positive relation between CLshare and future stock returns is an inter-industry effect, or it is likely that the dynamics hold intra-industry as well, i.e., after portfolios are neutralized with respect to their corresponding industry. To this end, I modify the portfolio assignment procedure to ensure that portfolios sorted on CLshare have similar industry characteristics by sorting industries into quintiles within each of the Fama-French 17 industries, which is the industry classification used in Zhang (2017). Pooling firms across the 17 industries, I then obtain quintile CLshare sorted portfolios that are now industry-neutralized. The results, reported in Panel I of Table 12, indicate that conducting the analysis based on this approach generates abnormal return spreads that are almost identical to the spread obtained using simple portfolio sort. Specifically, using the industry-neutralized portfolios, the high-minus-low CLshare portfolio generates an abnormal return of 8.67%, compared to 8.78% in the baseline setting. This suggests that the results are unlikely to be driven by unobserved sector-level characteristics that potentially induce difference in future returns.

[Table 12 about here]

4.3 Alternative Explanations

The Role of Labor Adjustment Costs

In their seminal paper, Merz and Yashiv (2007) show that in a market where labor adjustment is not costless, the labor becomes a quasi-fixed factor from which the firm can extract rents. As a result, labor becomes part of the firm value, which increases by the per unit labor adjustment cost. This implies that exogenous shocks that induce higher labor adjustment costs lead to an increase in the value of the firms with positive stock of labor. While in their model there is only one type of labor, their intuition can be extended to a framework where there are two types of labor with their respective adjustment costs. A shock that increases the adjustment cost associated with one type of labor can induce a differentially more positive increase in the value of the subset of firms that have a greater stock of that specific type of labor. This has potentially important implications for the question in this paper. A restrictive immigration policy shock can lead to an increase in the marginal labor adjustment costs associated with the type of labor with which skilled immigrants can compete, namely high-ISC occupations, consequently resulting in a relative increase in the value of high-CLshare firms, i.e. those with a greater share of high-ISC labor. Under the contrasting scenario where restrictive immigration policies are associated with states where the investors' marginal utility is lower, this implies that the value of high-CLshare firms covaries negatively with investors' marginal utility, therefore rendering these firms more risky. It is important to note that this alternative hypothesis cannot be ruled out by the findings from the GMM test in the previous section. Specifically if increases in the ImR are driven by restrictive immigration shocks as implied by this alternative explanation, the coefficient associated with the corresponding variable in the pricing kernel is still expected to have a positive sign if these shocks are associated with lower marginal utility for the representative consumer.

Using three sets of tests, I show that the observed risk premium is unlikely to be explained by this alternative hypothesis. I begin by examining the relation between the return to the ImR portfolio and the wage gap between high- and low-ISC occupations. As shown in Section 3, restrictive immigration policy shocks induce an increase in the wage associated with high-ISC occupations relative to low-ISC occupations. Under this alternative hypothesis, variations in the wage gap between the two occupation categories should therefore be positively correlated with the return to the ImR portfolio, as both of these values are positively affected by restrictive immigration policy shocks. To see if this is the case, I run the following regression

$$\Delta W_t = a_0 + b_0 R_{ImR,t} + b_1 R_{ImR,t-1} + b_2 R_{ImR,t-2} + c_0 R_{MKT,t} + c_1 R_{MKT,t-1} + \rho \Delta W_{t-1} + e_t \quad (10)$$

where ΔW_t is the annual growth in the difference between the logarithm of the employment-weighted average of the wage of the high-ISC occupations and that of the low-ISC occupations, $R_{ImR,t}$ is the annual return to the ImR portfolio, and $R_{MKT,t}$ is the annual market return. Following the approach adopted in Section 4.1, I construct the ImR portfolio returns by sorting industries into CLshare quintiles across all industries as well as within Fama-French 17 industries followed by averaging quintile returns across these industries (industry-neutralized return). I estimate the coefficients and the corresponding t-statistics associated with the contemporaneous as well as lagged values of ImR and the market portfolio return. I also report the results of an F-test for whether the sum of the coefficients associated with $R_{ImR,t}$, $R_{ImR,t-1}$, and $R_{ImR,t-2}$ are jointly equal to zero.

The results are reported in Table 13. I find that counter to this alternative hypothesis, the obtained estimates of the coefficients associated with the contemporaneous as well as the lagged returns to ImR portfolio are not positive. In contrast, and consistent with my hypothesis, the estimated coefficients b_1 and b_2 are in fact negative and statistically significant for both specifications. The observation that the negative sign is concentrated among the coefficients associated with the lagged ImR returns could be explained by the fact that wages are decided at the beginning of the year, although they are only observed at the end of the year (Eisfeldt and Papanikolou (2013)). The results of the F-test for the coefficients b_0, b_1 and b_2 indicate that the sum of the coefficients associated with ImR portfolio returns is negative and statistically different from zero. This suggests that increases in the wage gap between high- and low-ISC occupations are associated with a decline, and not an increase, in the return spread between the high- and low-CLshare firms, making the alternative hypothesis an unlikely explanation for the observed risk premium.

[Table 13 about here]

The risk premium for high-CLshare firms in the proposed alternative explanation is generated by increases in the values of these firms in response to restrictive immigration policy shocks under the assumption that such shocks are associated with reductions in the investors' marginal utility. In a second test, I test if this assumption about the representative investor's marginal utility is valid. In particular, I conduct a GMM test similar to the one discussed in Section 4, this time using the growth in wage gap between the high- and low-ISC occupations as a proxy for restrictive immigration policy shocks. Specifically, I estimate the coefficient associated with immigration policy shocks when the SDF is specified as

$$m = a - \gamma_m R_{MKT} - \gamma_w \Delta W, \tag{11}$$

where R_{MKT} is the market return and ΔW is the annual growth in the gap between the average wages of the high-ISC and low-ISC occupations. As before, I impose as moment restriction that the specified SDF should price the cross-section of Fama-French 30 industry portfolios. The average wage for each class of occupations is calculated by taking the occupational employment-weighted average wage across occupations in that class. Also, to make sure that the results are not driven by occupations that constitute a large share of employment in their corresponding class, I show the results where the average is calculated using equal weights. Finally, in an alternative specification, I use the characteristics-adjusted wage for each occupation when calculating the weighted average wage for each occupation class to ensure that the variations in the wage gap are above and beyond what could be explained by other occupation characteristics. The results are reported in Table 14. In contrast to the abovementioned hypothesis, the coefficient associated with the growth in the wage gap is negative and significant across different specifications, suggesting that restrictive immigration policy shocks that lead to a higher increase in the wages of high-ISC occupations relative to low-ISC occupations are priced negatively in the market.

[Table 14 about here]

As a final test to evaluate this alternative explanation, I conduct an event study by examining the price reaction of stocks to the public announcement of the "Buy American, Hire American Executive Order" on April 18, 2017. This order, aimed at protecting American workers and promoting employment rates for Americans, was perceived by the media upon its announcement as a policy that could lead to further restrictions on workers who qualify for H-1B visa program, and on the positions that could be filled by skilled immigrant workers.[10] The alternative hypothesis implies that in response to this event, firms with a greater share of workers employed in the high-ISC occupations should experience a positive price reaction, as the rents that can be extracted by these firms from workers in place increases by labor adjustment costs. To test if this is the case, I examine the relation between the cumulative return (CR) or cumulative abnormal return (CAR) of stocks over the days surrounding the announcement date with their corresponding CLshare. Specifically, I run a regression where the right hand side variable is the most recent CLshare for each stock, and the left hand side variable is its CR (CAR) over an event window that constitutes 1, 2 and 3 days before and after the announcement date. Throughout these specifications, I control for the same set of firm characteristics that were included in the above asset pricing tests. The results are reported in Table 15. Contrary to this hypothesis, the estimated coefficient associated with the CLshare is negative and significant throughout all of the event window, a finding that is consistent with restrictive immigration policy shocks inducing a decline, and not an increase, in the value of high-CLshare firms relative to their low-CLshare peers. Furthermore, motivated by the findings in Section 3.2, I test if the rigidity of wages induces variations in the relation between CR (CAR) and CLshare. To this end, I include in the above regression an interaction term between

[10]See, for instance https://www.nytimes.com/2017/04/18/technology/h1b-visa-facts-tech-worker.html

CLshare and a dummy variable that takes the value of one if the firm belongs to the highest tercile of all industries in terms of labor unionization. In line with my previous findings, I find that the negative relation between price changes and CLshare is in fact weakest among the subset of industries in which wages are least likely to change.

[Table 15 about here]

Overall, the results in this section substantiate my proposed channel, while suggesting that the observed return spread is unlikely to be driven by variations in labor adjustment cost for high-ISC occupations in response to immigration policy shocks.

ISC as a proxy for excess labor demand

The occupation-level immigrant skill compatibility measure in this paper is defined as the ratio of the total number of H-1B petitions for an occupation as a percentage of the total number of employees in that occupation. The assumption behind this measure is that for each occupation, the aggregate demand for workers is proportional to the total number of employees in that occupation. This way, the ratio compares the number of H-1B petitions across occupations adjusted for the demand for workers in that occupation. This assumption may not always be valid, especially during periods when there is large dispersion in industry growth rates that leads to excess demand for labor in a subset of industries. In this case, the cross-occupation variations in ISC index could be driven by the differences in the labor excess demand across occupations, rather than the fitness of the occupational skill requirements with those possessed by immigrants. As a result, what CLshare potentially captures is simply the relative demand for labor at the industry level, meaning that the observed return spread is explained by cross-industry variations in labor demand. Using direct industry-level measures for labor demand, I show that this is unlikely to be the case. To this end, I compare the expected excess returns of portfolios of industries ranked by their job openings rates, defined as the number of job openings as a percent of total employment plus job openings and is obtained from the BLS Job Openings and Labor Turnover Survey (JOLTS) dataset. Following the analysis in Section 1, I test the economic and statistical significance of the average return and abnormal returns of a portfolio that is long the highest quintile and short the lowest quintile of industries based on their ranking by their average job openings rate over the previous calendar year. For this portfolio, I examine the value-weighted as well as equally-weighted returns based on raw and unlevered stock returns. The results are presented in Panel A of Table 16. The expected return and the abnormal returns associated with this portfolio is negative and statistically insignificant across the board, which is different from the identified pattern between CLshare and expected returns. As illustrated in Panel B of Table 16, the results are similar when I use layoffs and discharge rate, defined as the number of layoffs and discharges as a percent of total employment, as a proxy for the (inverse) labor demand. This suggests that CLshare likely captures an industry characteristics that is distinct from the demand for labor, consistent with the low correlation between these variables reported in Table 4.

[Table 16 about here]

5 Conclusion

This paper introduces firms' ability to obtain human capital from the international labor market through immigration as a new firm characteristic that is priced in the cross section of equity returns. Using data obtained through FOIA containing information from all of the H-1B petitions filed with USCIS between 1997 and 2016, I quantify this characteristic by calculating the share of the industry's labor expenditure that is associated with occupations for which immigrant workers have compatible skills, and therefore are close substitutes to their native peers. I show that firms in industries with greater share of labor in immigrant skill compatible job have an annual abnormal return that is, on average, 8.8% higher that their peers that belong to industries in which this ratio is lowest. This return spread is economically and statistically significant, and is not explained by the commonly considered risk factors or the previously identified determinants of expected equity returns.

I propose that the observed spread reflects firms' differential exposure to shocks that affect firms' access to foreign skilled immigrants, namely, the immigration policy shocks. When wages are determined in a Nash bargain between workers and the firm, a shock that restricts skilled worker immigration reduces the supply of labor associated with the subset of occupations in which these workers can compete with native workers, leading to higher wages for this subset of jobs and consequently higher labor costs for firms that depend on these jobs. In a setting where more restrictive skilled worker immigration policy is associated with states with higher investor's marginal utility, a higher cash flow exposure to these shocks would induce higher expected return. I support my hypothesis by first showing that the supply of skilled immigrant workers is an important determinant of wages associated with occupations in which they can compete with native workers. To do this, I adopt a difference-in-differences estimation approach by exploiting the 2003 reduction in the legislative cap for the H-1B visa program. I show that as a result of this supply shock, wages associated with occupations in which skilled immigrants and native workers are close substitutes increased relative to an otherwise similar occupation, consequently raising labor expenditure for industries where such high compatibility occupations constitute a large share of labor expenditure, especially those in which wages are relatively less rigid. Accordingly, the observed immigration policy risk premium is concentrated among firms in industries where wages are least rigid. I also obtain GMM estimates for the market price of risk associates with immigration policy shocks, and find that restrictive immigration policy shocks are associated with an increase in investors' marginal utility. I also show that the identified return spread is unlikely driven by variations in labor adjustment costs in response to immigration policy shocks, or by the heterogeneity in labor demand across industries. Overall, results suggest that the ability to source skilled labor in the international labor market has important implications for equity returns.

Appendix

A. Sample Construction

Financial and Accounting Data

Monthly stock data is from the Center for Research in Security Prices (CRSP). The sample is limited to common stocks (SHRCD=10 or 11) that are listed on NYSE, NASDAQ or AMEX (EXCHCD=1, 2 or 3). Accounting data is from Compustat's Fundamental Annual files. Unless otherwise specified, micro-cap firms, defined as firms with capitalization in the bottom 20th size quintile are excluded from the sample. Also reduce the influence of potential outliers, each firm level accounting variable is winsorized at the 1% level on each tail in each sample year. The firm-level characteristics based on accounting data are as follows:

- *Size* is defined as the natural logarithm of the firm's market capitalization.
- *BM* is the natural logarithm of the firm's book value to market equity, following Fama and French (1992).
- *OpLev* is the firm's operating leverage, defined as the cost of goods sold (COGS) plus selling, general and administrative expense (XSGA) divided by the total assets (AT).
- *IK* is the investment to capital ratio, and is defined as capital expenditures (CAPX) divided by the net property, plant, and equipment (PPENT).
- *MktLev* is the firm's financial leverage, defined as the ratio of total debt to market value of firm, following Fan, Titman, and Twite (2012). Total debt is the total of the long-term interest bearing debt (DLTT) and the book value of short-term debt (DLC). Market value of firm is defined as the market value of common equity as defined in Fama and French (1992), plus total debt, plus book value of preferred stock (PSTK).
- *FCF* is the firm's free cash flow to book equity, following Novy-Marx (2013). Free cash flow is the total of net income (NI) and depreciation and amortization (DP) minus capital expenditure (CAPX) minus changes in working capital (WCAPCH).

- *Prof* is the firm's profitability, defined following Novy-Marx (2013) as the total revenue (REVT) minus cost of goods sold (COGS) divided by total assets (AT).

- *HN* is the hiring rate, defined following Belo et al. (2014) as the ratio of one year change in total number of employees (EMP) in year t divided by the average number of employees in year t and year $t-1$.

- *Innov* is the measure of firm's innovation, which is proxied by the citation-weighted value of the firm's patents based on the method proposed by Kogan, Papanikolaou, Seru, and Stoffman (2017). The data is downloaded from Amit Seru's website.

- β^M is the conditional market beta, calculated for each firm-year by regressing its monthly excess equity return on the market excess return over a window the most recent 36 months.

- β^{EPU} is the exposure to changes in the economic policy uncertainty (EPU) index, calculated for each firm by regressing its monthly excess return on the monthly changes in the EPU index obtained from Baker et al. (2016).[11]

Occupation Characteristics

The data for the occupational characteristics is from the Occupational Information Network (O*NET) dataset, which contains a set of variables that describe numerous characteristics of more than 900 occupations in the economy. The job characteristics used in this study are constructed by combining scores associated with the relevant job attributes from this dataset. For the job attributes that are classified as work activity, O*NET provides information on the "importance" and "level" of the activity in each occupation. I follow Firpo, Fortin, and Lemieux (2013) and Blinder (2009) by combining these quantities using a Cobb-Douglas function with the arbitrary weights of one third for the "level" quantities and two third for the "importance" quantities. For the elements categorized as "work contexts" that represent the frequency of activities, I multiply the value of the level with the frequency of the activity to obtain a unique score for the subject attribute. I then rescale scores associated with each attribute to range between 0 and 1. The list of job characteristics and how they are constructed using the O*NET job attributes is as follows:

[11] The results remain virtually unchanged if I include the market excess return on the right hand side of the regression as well.

- *Skill* is the extent of preparation required for the job, as measured by the Job Zones variable in O*NET.

- *Routine* measures the ease with which the job can be automated, and is constructed following Firpo et al. (2013) by adding the scores associated with the degree of automation (4.C.3.b.2), importance of repeating same task (4.C.3.b.7), negative of structured versus unstructured work (4.C.3.b.8), pace determined by the speed of equipment (4.C.3.d.3), and spending time making repetitive motions (4.C.2.d.1.i).

- *Info* is the information content of the job constructed based on the definition proposed in Jensen and Kletzer (2010) by adding scores associated with Getting Information (4.A.1.a.1), Processing Information (4.A.2.a.2), Analyzing Data or Information (4.A.2.a.4), Interacting With Computers (4.A.3.b.1), and Documenting/Recording Information (4.A.3.b.6).

- *Offshorability* is the ease with which a job can be relocated abroad, and is defined following Acemoglu and Autor (2011) as reverse of the sum of the scores associated with the following elements: Face-to-Face Discussions (4.C.1.a.2.l), Assisting and Caring for Others (4.A.4.a.5), Performing for or Working Directly with the Public (4.A.4.a.8), Inspecting Equipment, Structures, or Material (4.A.1.b.2), Handling and Moving Objects (4.A.3.a.2), Repairing and Maintaining Mechanical Equipment (4.A.3.b.4), Repairing and Maintaining Electronic Equipment (4.A.3.b.5).

- *Social* is the extent to which a job requires social skills, and is constructed following Deming (2017) by summing the scores associate with Social Perceptiveness (2.B.1.a), Coordination (2.B.1.b), Persuasion (2.B.1.c), Negotiation (2.B.1.d).

Finally, to make the scores of different job characteristic comparable, I rescale each attribute across jobs to values between 0 and 1.

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Table 1: **List of Occupations with Highest Average Immigrant Skill Compatibility Index** The table presents the list of occupations with the highest average Immigrant Skill Compatibility index (ISC) from 1997 and 2016, where the index is defined for each occupation-year as the ratio of the number of H1B petitions for an occupation with the proposed start date in that year to the total number of employees in that occupation-year. The ranking includes occupations that are present in the matched Compustat-OES dataset in each year. Occupations are classified by their 2010 five-digit Standard Occupation Codes (SOC).

rank	SOC	Occupation Title	Compatibility Index
1	19-2010	Astronomers and Physicists	0.051
2	15-1110	Computer and Information Research Scientists	0.039
3	19-4020	Biological Technicians	0.032
4	15-1130	Software Developers and Programmers	0.030
5	41-9030	Sales Engineers	0.029
6	11-9040	Architectural and Engineering Managers	0.027
7	11-1010	Chief Executives	0.022
8	19-1040	Medical Scientists	0.022
9	15-1120	Computer and Information Analysts	0.021
10	19-1020	Biological Scientists	0.020
11	19-3040	Sociologists	0.020
12	19-4010	Agricultural and Food Science Technicians	0.019
13	19-1010	Agricultural and Food Scientists	0.019
14	19-1090	Miscellaneous Life Scientists	0.017
15	15-2020	Mathematicians	0.016
16	15-2040	Statisticians	0.016
17	15-2010	Actuaries	0.016
18	15-2030	Operations Research Analysts	0.016
19	19-4030	Chemical Technicians	0.016
20	17-2070	Electrical and Electronics Engineers	0.015

Table 2: **Immigrant Skill Compatible Occupations**

Panel A presents the time-series average of the correlation between Immigrant Skill Compatibility index (ISC) and other occupational characteristics. ISC is defined as the ratio of the number of H1B petitions for an occupation with the proposed start date in a given year to the total number of employees in that occupation-year. Skill represents the score associated with the Specific Vocational Preparation as measured by O*NET. Routineness represents the propensity at which the job can be automated, and Offshorability is the ease with which the occupational tasks can be performed in a foreign country, both constructed based on Acemoglu and Autor (2011). Social is the score associated with the required social skill for the job, defined as in Deming (2017). Information is the information content intensity of the occupation, measured based on Firpo et al. (2013). See the Appendix for further explanation of these variables. Panel B reports the time-series average of the share of Immigrant Skill Compatible labor and the H-1B concentration across major occupational groups defined based on the OES taxonomy classification. The H-1B concentration is defined as the ratio of the number of H-1B petitions filed for an occupation in a given year divided by the total number of H-1B petitions in that year. Immigrant Skill Compatible occupations are defined as the subset of occupations that are ranked in the top quartile in terms of Immigrant Skill Compatibility index (ISC) across all occupations in the Occupational Employment Statistics dataset in that year. For the years between 1999 and 2015, in which the Standard Occupational Classification (SOC) classification is used for occupations, I follow the suggestions of the SOC Revision Policy Committee by aggregating the major SOC classification to seven aggregate groups: Management represents managerial and administration occupations (SOC 11-13). Professional represents professional, paraprofessional, and technical occupations (SOC 15-31). Service represents service and related occupations (SOC 33-39). Sales represents sales-related occupations (SOC 41). Clerk represents office, clerical, and administrative support occupations (SOC 43). Agriculture represents farming, fishing, and forestry occupations (SOC 45). Production represents production, maintenance, construction, and transportation occupations (SOC 47-53).

Table 2. Continued

Panel A: Correlation between ISC and other Job Characteristics

	ISC	Skill	Routine	Offshorability	Social	Info
ISC	1.000	0.252	-0.159	0.283	0.027	0.223
Skill	0.252	1.000	-0.442	0.333	0.618	0.728
Routine	-0.159	-0.442	1.000	-0.179	-0.387	-0.143
Offshorability	0.283	0.333	-0.179	1.000	0.125	0.254
Social	0.027	0.618	-0.387	0.125	1.000	0.546
Information	0.223	0.728	-0.143	0.254	0.546	1.000

Panel B: H-1B Concentration and Immigrant Skill Compatible Labor across Major Occupation Groups

	Management	Professional	Sales	Clerk	Service	Agriculture	Production
H-1B Concentration (%)	34.1%	60.9%	1.5%	0.9%	0.1%	0.3%	4.8%
ISC (%)	37.1%	28.8%	2.0%	1.3%	0.1%	7.7%	5.0%

Table 3: **List of Industries with Highest and Lowest**

The table presents the list of industries with the highest and lowest CLshare in 2016. CLshare is defined as the ratio of the industry's total labor expense on its Immigrant Skill Compatible labor to its total labor expense. Industries are defined based on 4-digit North American Industry Classification System (NAICS) classification.

Panel A: Industries with Lowest and Highest CLshare in 2016

Rank	NAICS	Industry	CLshare
		Industries with Highest CLshare	
1	541300	Architectural, Engineering, and Related Services	0.711
2	525900	Other Investment Pools and Funds	0.690
3	541700	Scientific Research and Development Services	0.626
4	611300	Colleges, Universities, and Professional Schools	0.626
5	541200	Accounting, Tax Preparation, Bookkeeping, and Payroll Services	0.616
6	541400	Specialized Design Services	0.611
7	523900	Other Financial Investment Activities	0.567
8	711500	Independent Artists, Writers, and Performers	0.559
9	334400	Semiconductor and Other Electronic Component Manufacturing	0.540
10	446100	Health and Personal Care Stores	0.538
		Industries with Lowest CLshare	
1	722500	Restaurants and Other Eating Places	0.004
2	722400	Drinking Places (Alcoholic Beverages)	0.012
3	812100	Personal Care Services	0.016
4	487900	Scenic and Sightseeing Transportation, Other	0.018
5	448200	Shoe Stores	0.019
6	447100	Gasoline Stations	0.020
7	448100	Clothing Stores	0.020
8	722300	Special Food Services	0.024
9	445300	Beer, Wine, and Liquor Stores	0.027
10	485400	School and Employee Bus Transportation	0.028

Table 4: **Summary Statistics for** CLSHARE

The table presents the summary statistics of CLSHARE as a firm characteristics, where the firm CLSHARE is defined as the ratio of its corresponding industry's total Immigrant Skill Compatible labor cost to its total labor cost. Panel A shows the mean and standard deviation of CLSHARE for the firms in each sector, where sectors are defined based on firms' SIC classification as follow: Agriculture, Forestry and Fishing (SIC between 0100 and 0999), Mining (SIC between 1000 and 1499), Construction (SIC between 1500 and 1799), Manufacturing (SIC between 2000 and 3999), Transportation, Communications, Electric, Gas and Sanitary service (SIC between 4000 and 4999), Wholesales Trade (SIC between 5000 and 5199), Retail Trade (SIC between 5200 and 5999), Finance, Insurance and Real Estate (SIC between 6000 and 6799), Services (SIC between 7000 and 8999), and Public Administration (SIC between 9100 and 9729). Panel B reports the equally weighted average of firm characteristics and market moments for portfolios of firms sorted into quintiles based on CLSHARE. *BM* is the book-to-market ratio. *Size* is the firm's market capitalization. *OpLev* is the operating leverage. *IK* is the investment-to-capital ratio. *MktLev* is the financial leverage. *Prof* is the firm's profitability. *HN* is the firm's hiring rate. *Patent* is firms' patent value. *Skill* is the share of skilled labor expenses, where skilled labor is defined as those in occupations with skills scores that are in the upper quartile of occupations. Similarly, *Routine*, *Social*, *Information* and *Offshorability* are the industry's share of labor expenses associated with occupations that are, respectively, in the upper quartile of all occupations in terms of routineness, social skill intensity, information content, and offshorability. Variables are winsorized at the 1% level in each tail of the distribution. Job Openings Rate is the number of job openings by the sum of employment and job openings in the industry. Layoffs Rate is the number of layoffs by employment in the industry. See the Appendix for more details on the definition of variables. Expected excess returns are the average annual returns in excess of one-month treasury bill rates over the next 12 month for portfolios sorted on CLSHARE. Panel C shows the firms' transition probability from one CLSHARE quintile to another over a one year period.

Panel A: Firm CLSHARE by Sector

	Agri	Mining	Const	Manuf	Trans	Whole	Retail	Finance	Services	Publ. Adm.
Mean	0.250	0.352	0.116	0.408	0.262	0.264	0.105	0.307	0.449	0.247
Std.	0.180	0.157	0.107	0.170	0.140	0.123	0.123	0.086	0.264	0.207

Table 4. Continued.

Panel B: Firm Characteristics and Returns in Portfolios Sorted by CLSHARE

	Low	2	3	4	High	Hi-Lo
Portfolio Characterstics						
CLSHARE	0.109	0.246	0.318	0.450	0.626	
BM	0.824	0.638	0.795	0.565	0.523	
Size	5.836	5.780	5.641	5.647	5.426	
OpLev	1.285	0.925	0.428	0.840	0.885	
IK	0.273	0.323	0.280	0.384	0.477	
MktLev	0.292	0.275	0.352	0.177	0.106	
Prof	0.205	0.172	0.125	0.031	-0.041	
HN	0.039	0.043	0.053	0.047	0.049	
Patent	2.311	7.690	4.717	16.402	30.582	
Skill	0.035	0.074	0.103	0.110	0.117	
Routine	0.262	0.330	0.344	0.258	0.171	
Social	0.348	0.373	0.391	0.390	0.347	
Information	0.095	0.230	0.298	0.329	0.442	
Offshorability	0.214	0.411	0.528	0.396	0.503	
Job Openings Rate	2.228	2.455	2.772	2.267	2.473	
Layoffs Rate	1.951	1.299	0.788	1.284	1.420	
Portfolio Returns						
Expected Excess Returns (%)	9.160	11.904	11.588	10.004	13.608	4.45

Panel C: Transition Probabilities across Portfolios Sorted by CLSHARE

	Q1(t)	Q2(t)	Q3(t)	Q4(t)	Q5(t)
Q1(t-1)	0.875	0.096	0.017	0.007	0.004
Q2(t-1)	0.104	0.641	0.227	0.021	0.006
Q3(t-1)	0.016	0.214	0.652	0.113	0.004
Q4(t-1)	0.009	0.042	0.081	0.739	0.130
Q5(t-1)	0.005	0.015	0.017	0.113	0.849

Table 5: **Returns of Portfolios Sorted on** CLshare

This table reports α over a five-factor Fama-French model of portfolios, along with their corresponding factor loadings, of stocks ranked on the basis of their CLshare at the end of the previous June, where mid-CLshare portfolio is formed by pooling stocks in the second, third and the fourth quintiles. Panel A presents returns for equally weighted portfolio, while Panel B reports value weighted returns for portfolios that are held for 12 months without rebalancing. Monthly returns in excess of one month treasury bill rates are regressed against on the market minus risk free rate (MKT), the value factor (HML), the size factor (SMB), the profitability factor (RMW), and the investment factor (CMA), all obtained from Kenneth French's website. Unlevered returns are the returns adjusted for market leverage following Donangelo (2014). Monthly returns are annualized by multiplying to 12, and are presented in percentages. Significance levels are denoted by * for 1%, ** for 5%, and *** for 10%, respectively, and is used for the alpha associated with the returns of the Hi-Lo portfolio to preserve space. The sample period for returns is from July 1998 to December 2017.

Table 5. Continued

Panel A: Equally Weighted Returns

	Raw returns				Unlevered returns			
	Low	Mid	High	Hi-Lo	Low	Mid	High	Hi-Lo
α	-0.945	3.216	7.834***	8.779***	-1.344	2.228	7.008***	8.352***
	(-0.391)	(2.359)	(3.088)	(3.396)	(-0.812)	(2.393)	(3.167)	(3.828)
β^{MKT}	1.035***	0.878	1.079***	0.044	0.730	0.613	0.931***	0.201***
	(19.615)	(29.486)	(19.467)	(0.774)	(20.188)	(30.134)	(19.255)	(4.22)
β^{HML}	0.770***	0.593	0.754***	-0.016	0.531***	0.442	0.645***	0.115*
	(11.001)	(15.018)	(10.262)	(-0.21)	(11.064)	(16.362)	(10.059)	(1.812)
β^{SMB}	0.476***	0.423	-0.138	-0.615***	0.255***	0.222	-0.176**	-0.431***
	(5.555)	(8.753)	(-1.538)	(-6.700)	(4.343)	(6.710)	(-2.242)	(-5.567)
β^{RMW}	0.227**	-0.038	-0.650	-0.877***	0.221***	0.008	-0.569***	-0.789***
	(2.492)	(-0.738)	(-6.781)	(-8.982)	(3.534)	(0.222)	(-6.805)	(-9.581)
β^{CMA}	-0.127	-0.190	-0.160	-0.033	-0.058	-0.143	-0.127	-0.069
	(-1.055)	(0.904)	(-1.266)	(-0.256)	(-0.708)	(0.907)	(-1.155)	(-0.634)

Panel B: Value Weighted Returns

	Raw returns				Unlevered returns			
	Low	Mid	High	Hi-Lo	Low	Mid	High	Hi-Lo
α	-2.793	-0.307	2.289*	5.082**	-2.105	0.016	2.169*	4.273*
	(-1.426)	(-0.359)	(1.891)	(2.035)	(-1.258)	(0.022)	(1.885)	(1.943)
β^{MKT}	0.982***	0.967	1.070***	0.088	0.774***	0.699	0.956***	0.182***
	(22.951)	(51.748)	(40.474)	(1.62)	(21.183)	(43.978)	(38.062)	(3.79)
β^{HML}	0.174***	-0.081	0.053	-0.121*	0.107**	-0.055	0.031	-0.076
	(3.069)	(-3.262)	(1.506)	(-1.677)	(2.206)	(-2.628)	(0.935)	(-1.190)
β^{SMB}	0.001	0.273	-0.302 ***	-0.303***	-0.002	0.114	-0.297***	-0.295***
	(0.01)	(8,984)	(-7.035)	(-3.418)	(-0.032)	(4.399)	(-7.282)	(-3.784)
β^{RMW}	0.521***	0.122	-0.141***	-0.662***	0.407***	0.164	-0.156***	-0.563***
	(7.046)	(3.779)	(-3.088)	(-7.024)	(6.443)	(5.986)	(-3.596)	(-6.783)
β^{CMA}	0.093	0.096	-0.134**	-0.227*	0.049	0.047	-0.156**	-0.205*
	(0.954)	(2.266)	(-2.223)	(-1.826)	(0.593)	(1.309)	(-2.723)	(-1.875)

Table 6: **Fama-MacBeth Regressions of Monthly Stock Returns**

This table reports the results of monthly Fama-MacBeth regressions. Stock returns in each month are regressed on the most recent values of CLshare, log book-to-market ratio (BM), log market capitalization (Size), conditional beta estimated based on return over a window of the past 36 months (β^M), profitability (Prof), free cash flow (FCF), market leverage (MktLev), operating leverage (OpLev), hiring rate (HN), routineness (Routine), offshorability (Off) and the exposure to economic policy uncertainty shocks (β^{EPU}). See the Appendix for more details on the definition of variables. Reported are the average coefficients and the corresponding t-statistics. Significance levels are denoted by * for 1%, ** for 5%, and *** for 10%, respectively.

Reg	CLshare	BM	Size	β^M	Prof	FCF	MktLev	OpLev	HN	Routine	Off	β^{EPU}
(1)	0.018**											
	(2.056)											
(2)	0.022***	0.003***										
	(2.839)	(3.417)										
(3)	0.015*		-0.005***									
	(1.861)		(-8.863)									
(4)	0.013**			0.002								
	(2.043)			(0.853)								
(5)	0.017**				0.001							
	(1.999)				(0.319)							
(6)	0.016*					-0.005***						
	(1.931)					(-3.266)						
(7)	0.019**						0.001					
	(2.537)						(0.395)					
(8)	0.021**							0.005***				
	(2.373)							(6.136)				
(9)	0.019**								-0.015			
	(2.406)								(-6.256)			
(10)	0.017**									-0.004		
	(2.062)									(-0.748)		
(11)	0.021**										-0.008**	
	(2.235)										(-2.010)	
(12)	0.016**											-0.006
	(2.066)											(-0.989)
(13)	0.014***	0.001	-0.004***	0.001	0.003	-0.004***	0.000	0.002***	-0.009***	0.001	-0.002	0.001
	(2.730)	(0.856)	(-6.333)	(0.465)	(1.156)	(-2.926)	(-0.033)	(3.42)	(-5.554)	(0.386)	(-0.673)	(0.315)

Table 7: **Effect of H-1B Cap Drop on Wages - Time Series Dynamics**
This table provides the estimation results from the OLS regression $wage_{jit} = \gamma_j + \lambda_t + \sum_{2000<k<2004} \beta_k \cdot ISC_j \cdot \tau_{t,k} + \beta \cdot ISC_j \cdot Post_t + \delta \cdot X_j \cdot Post_t + \epsilon_{jt}$, where ISC_j is a dummy variable that takes on a value of 1 if the Immigrant Skill Compatibility index for occupation j is in the top 25% of all occupations at the end of year 2002, and zero otherwise. $\tau_{t,k}$ denotes a dummy variable that takes on the value of 1 if $t = i$, and zero otherwise. Similarly, $Post_t$ is a dummy variable that takes on a value of 1 if year t is in the post-treatment period. X_j is the set of occupation-level control variables, which include Skill, Routineness and Social Skill intensity, all represented as a dummy variable that take on a value of 1 if the occupation is among the top quartile of all occupations in terms of the corresponding job characteristics. In Columns (1)-(4), $wage_{jit}$ is the log annual average wage associated with occupation j in industry i in year t. In Columns (5)-(6), $wage_{jit}$ is the characteristics-adjusted wage associated with occupation j in industry i in year t, which is obtained as the residual ϵ_{jit} from the panel regression $w_{jit} = c + \lambda_{it} + \delta \cdot X_j + \epsilon_{jit}$ where X_j are the occupation control variables Skill, Routineness, Social Skill intensity and Offshorability, and w_{jit} is the log annual average wage associated with occupation j in industry i in year t. The sample period is limited to 2000-2007 to include the pre-treatment period 2000-2003, thus making the year 2000 the baseline period for the comparison of the wage-gap between occupations. Standard errors are clustered at the occupation level, and the corresponding t-statistics are reported in parenthesis. Significance levels are denoted by * for 1%, ** for 5%, and *** for 10%, respectively.

	Raw wage				Adjusted wage	
	(1)	(2)	(3)	(4)	(5)	(6)
ISC$\times\tau_{t,2001}$	-0.00237	-0.00382	-0.00250	-0.00440	-0.00136	-0.00173
	(-0.478)	(-0.751)	(-0.617)	(-1.009)	(-0.413)	(-0.499)
ISC$\times\tau_{t,2002}$	0.00981	0.0115	0.00318	0.00480	0.00674	0.00560
	(1.101)	(1.303)	(0.504)	(0.781)	(1.107)	(0.893)
ISC$\times\tau_{t,2003}$	0.0217**	0.0226**	0.0105	0.0120*	0.00795	0.00729
	(2.247)	(2.386)	(1.635)	(1.943)	(1.242)	(1.127)
ISC×Post	0.0408***	0.0401***	0.0260***	0.0278***	0.0137*	0.0135*
	(3.979)	(4.013)	(3.274)	(3.590)	(1.899)	(1.843)
FE	Yr, Occ	Ind×Yr, Occ	Yr, Occ	Ind×Yr, Occ	Yr, Occ	Ind×Yr, Occ
Controls	No	No	Yes	Yes	–	–
Obs.	343,817	343,817	343,817	343,817	334,199	334,199

Table 8: **Effect of H-1B Cap Drop on Wages**

This table reports the results of the difference-in-differences test showing the differential effect of the H-1B cap drop on wages of occupations with varying levels of Immigrant Skill Compatibility. Specifically, it provides the estimation results from the OLS regression $wage_{jit} = \gamma_j + \lambda_t + \beta \cdot ISC_j \cdot Post_t + \delta \cdot X_j \cdot Post_t + \epsilon_{jt}$, where $wage_{jit}$ is the log annual average wage associated with occupation j in industry i in year t ISC_j is a dummy variable that takes on a value of 1 if the Immigrant Skill Compatibility index for occupation j is in the top 25% of all occupations at the end of 2002, and zero otherwise. $Post_t$ represents a dummy variable that takes on a value of 1 if year t is in the post-treatment period 2004-2016. X_j is the set of occupation-level control variables, which include Skill, Routineness and Social Skill intensity, all represented as a dummy variable that take on a value of 1 if the occupation is among the top quartile of all occupations in terms of the corresponding job characteristics. Standard errors are clustered at the occupation level, and the corresponding t-statistics are reported in parenthesis. Significance levels are denoted by * for 1%, ** for 5%, and *** for 10%, respectively. The sample period is from 1997 to 2016.

	(1)	(2)	(3)	(4)	(5)	(6)
ISC×Post	0.066***	0.041***	0.062***	0.0410***	0.020***	0.014**
	(5.430)	(4.592)	(5.164)	(4.645)	(3.590)	(2.490)
FE	Yr, Occ	Yr, Occ	Ind×Yr, Occ	Ind×Yr, Occ	Yr, Ind×Occ	Yr, Ind×Occ
Controls	No	Yes	No	Yes	No	Yes
Obs.	981,809	981,809	981,806	981,806	963,502	963,502

Table 9: **Effect of H-1B Cap Drops on Labor Expenditure**

This table shows the response of labor expenditure to the H-1B cap drop in 2003. Specifically, it provides the estimation results from the OLS regression $Exp_{it} = \gamma_i + \lambda_t + \beta \cdot \text{CL}\textsc{share}_i \cdot Post_t + \delta_1 \cdot Union_{i,t} + \delta_2 \cdot Union_{i,t} \cdot Post_t + \delta_3 \cdot \text{CL}\textsc{share}_i \cdot Union_{i,t} + \delta_4 \cdot \text{CL}\textsc{share}_i \cdot Union_{i,t} \cdot Post_t + \delta_5 \cdot X_{i,t} \cdot Post_t + \epsilon_{it}$, where CLSHARE$_i$ is a dummy variable that is equal to 1 if the firm belongs to industries in the highest CLSHARE quintile at the end of 2002. $Post_t$ is a dummy variable that takes on a value of 1 if year t is in the post-treatment period, and zero otherwise. $Union_{i,t}$ is a dummy variable that takes on a value of 1 if the industry to which the firm belongs to is in the top quintile of industries in terms of labor unionization, and zero otherwise. We use three sets of proxies for labor expenditure (X_{it}): W_{it}^m is the hourly median wage in the industry to which the firm belongs; W_{it}^{emp} is the employment-weighted average of the hourly wages across all occupations in the industry to which the firm belongs; LC_{it} is the total labor costs in the industry to which the firm belongs, defined as the product of the employment and the associated wage in each occupation in industry i, aggregated across occupations in that industry. All specifications include year and firm fixed effect, with standard errors that are clustered at the industry level. The corresponding t-statistics are reported in parenthesis. Significance levels are denoted by * for 1%, ** for 5%, and *** for 10%, respectively.

Dep. Var.	W_{it}^m		W_{it}^{emp}		LC_{it}	
	(1)	(2)	(3)	(4)	(5)	(6)
CLSHARE ×Post	0.0594***	0.0563**	0.0454**	0.0441**	0.0459*	0.0507**
	(2.665)	(2.545)	(2.048)	(2.025)	(1.705)	(2.002)
Union		0.0299***		0.00724		-0.0705*
		(3.658)		(0.665)		(-1.815)
Union×Post		-0.0381***		-0.0205**		-0.0264
		(-3.993)		(-2.190)		(-0.884)
CLSHARE ×Union		0.0798***		0.0322*		1.122***
		(3.955)		(1.717)		(28.06)
CLSHARE ×Post×Union		-0.0840***		-0.0628**		-1.504***
		(-2.907)		(-1.972)		(-4.295)
Obs.	18,629	18,629	13,638	13,638	13,638	13,638

Table 10: **CLshare and Portfolio Returns - Testing the Channel**

This table reports the result of a panel regression of monthly stock returns on lagged CLSHARE and its interaction with a number of industry characteristics. CLSHARE is the share of the firm's total labor costs that are associated with Immigrant Skill Compatible occupations. Panel A reports the results for a specification with no interaction terms (Column 1-4) and a specification which includes the interaction between CLSHARE and *Union* (Columns 5-8). *Union* is a dummy variable that is equal to one if the industry to which the firm belongs is in the top quartile of industries in terms of labor unionization and zero if it is in the bottom quartile, where labor unionization is defined as the percent of employed workers who are covered by a collective bargaining agreement. Panel B reports the results for specification where CLSHARE is interacted with *Skill* (Columns 1-4) and *Social Skill Intensity* (Columns 5-8). *Skill* (*Social*) is a dummy variable that is equal to one if the industry to which the firm belongs is in the top quartile of industries in terms of the share of high skilled (high social skill) labor expenditure and zero if it is in the bottom quartile. Firm controls are the same as those in Table 8. In the even columns, the industry-year fixed effect is based on the Fama-French 17 industry classification. Following Petersen (2009), the standard errors are clustered by industry and year, and the corresponding *t*-statistics are reported in parenthesis. Significance levels are denoted by * for 1%, ** for 5%, and *** for 10%, respectively. The sample period covers stock returns from July 1998 to December 2017.

Panel A: Portfolio Returns and Labor Unionization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CLSHARE	0.0198	0.0173*	0.0142**	0.0139***	0.0274	0.0267**	0.0236**	0.0191**
	(1.369)	(1.693)	(2.591)	(3.369)	(1.493)	(1.974)	(2.260)	(2.210)
CLSHARE × Union					-0.0382**	-0.0332**	-0.0367**	-0.0245*
					(-2.792)	(-2.581)	(-2.159)	(-1.690)
Union					0.00919**	0.00556	0.00871*	0.00348
					(2.106)	(1.319)	(1.924)	(0.731)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Fixed Effect	Yr	Ind×Yr	Yr	Ind×Yr	Yr	Ind×Yr	Yr	Ind×Yr

Panel B: Portfolio Returns, Training and Social Skills

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CLSHARE	-0.00580	-0.0209*	-0.0188***	-0.0158	0.0207	0.0259*	0.0141*	0.0236***
	(-0.516)	(-1.798)	(-3.131)	(-1.604)	(1.407)	(1.850)	(1.702)	(3.064)
CLSHARE × Skill	0.0691***	0.0682***	0.0770***	0.0585**				
	(3.594)	(2.890)	(3.997)	(2.358)				
Skill	-0.0174**	-0.0142**	-0.0159***	-0.0118*				
	(-2.624)	(-2.057)	(-2.730)	(-1.794)				
CLSHARE × Social					-0.0238*	-0.0211*	-0.0244**	-0.0249**
					(-1.851)	(-1.700)	(-2.118)	(-2.432)
Social					0.00275	0.00188	0.00526*	0.00328
					(0.935)	(0.955)	(1.846)	(1.415)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Fixed Effect	Yr	Ind×Yr	Yr	Ind×Yr	Yr	Ind×Yr	Yr	Ind×Yr

Table 11: **Estimating the Market Price of Immigration Policy Shocks**

This table provides estimates of the parameters of the stochastic discount factor using the Generalized Method of Moments and the cross-section of Fama-French 30 industry portfolios. We use four sets of proxies for shocks to immigration policy shocks: first, the risk-adjusted return to the ImR portfolio (R^{e}_{ImR}); second, the risk-adjusted return to the industry-neutralized ImR portfolio ($R^{\mathrm{e,IN}}_{ImR}$); third, the return to the ImR portfolio (R_{ImR}); and fourth, the return to the industry-neutralized ImR portfolio (R^{IN}_{ImR}). Columns (1) and (2) show results for the pricing kernel specification with market and immigration policy shocks, while columns (3) and (4) show results for pricing kernel specification based on Fama-French five factor specification plus the immigration policy shock (see Section 4 for details). The corresponding t-statistics are reported in parenthesis. Significance levels are denoted by * for 1%, ** for 5%, and *** for 10%, respectively.

Factor	(CAPM)	(1)	(2)	(3)	(4)
R_{MKT}	0.182**	0.209***	0.215***	0.386***	0.386***
	(2.461)	(2.871)	(2.948)	(3.724)	(3.928)
R^{e}_{ImR}		0.155*			
		(1.797)			
$R^{\mathrm{e,IN}}_{ImR}$			0.243**		
			(2.256)		
R_{ImR}				0.402**	
				(2.258)	
R^{IN}_{ImR}					0.602**
					(2.492)
Hansen J-Statistics	21.313	20.244	19.392	17.698	16.219

Table 12: **Portfolio Sorts - Robustness Test**

This table reports α over a five-factor Fama-French model of equally-weighted portfolios of stocks ranked into quintiles on the basis of the value of their CLshare at the end of the previous June, where mid-CLshare portfolio is formed by pooling stocks in the second, third and the fourth quintiles. Monthly returns in excess of one month treasury bill rates are regressed against on the market minus risk free rate (MKT), the value factor (HML), the size factor (SMB), the profitability factor (RMW), and the investment factor (CMA), all obtained from Kenneth French's website. Unlevered returns are the returns adjusted for market leverage following Donangelo (2014). Panel A. reports benchmark results. In Panel B., returns are adjusted for size, book-to-market and past returns based on the methodology in Daniel et al. (1997). In Panel C., CLshare is constructed as labor-cost weighted average of Skilled Immigrant Skill Compatibility index (ISC). In Panel D., CLshare is constructed using occupational employment of the industry as the weight. In Panel E., Immigrant Skill Compatible occupations are defined as those that belong to the upper quintile of all occupations in terms of ISC. In Panel F., micro-cap firms are retained. In Panel G., micro-cap firms are dropped from the sample, while they are defined as those firms that belong to the in the bottom NYSE size quintile at the end of the previous December. Panel H. reports the results when financial firms (SIC between 6000 and 6999) are excluded from the sample. In Panel I., firms are sorted within their corresponding Fama-French 17 industries, and the resulting return for each is calculated as the equally weighted return associated with that quintile across industries. In all panels, monthly returns are annualized by multiplying to 12, and are presented in percentages. Significance levels are denoted by * for 1%, ** for 5%, and *** for 10%, respectively, and is used for the coefficients associated with the returns of the Hi-Lo portfolio to preserve space. The sample period for returns is from July 1998 to December 2017.

Table 12. Continued

	Levered				Unlevered			
	Low	Mid	High	Hi-Lo	Low	Mid	High	Hi-Lo
A. Benchmark								
α	-0.945	3.216**	7.834***	8.779***	-1.344	2.228**	7.008***	8.352***
t-statistic	(-0.391)	(2.359)	(3.088)	(3.396)	(-0.812)	(2.393)	(3.167)	(3.828)
B. DGTW-adjusted returns								
α	-6.557***	-2.470***	1.392	7.949***	-6.557***	-2.470***	1.392	7.949***
t-statistic	(-4.032)	(-3.82)	(1.427)	(3.572)	(-4.032)	(-3.82)	(1.427)	(3.572)
C. CLshare constructed based on continuous value of ISC								
α	-2.004	3.365**	6.937***	8.941***	-2.151	2.517***	6.13***	8.282***
t-statistic	(-0.819)	(2.367)	(2.787)	(3.556)	(-1.241)	(2.621)	(2.867)	(3.903)
D. CLshare constructed based on occupational employment level								
α	-0.442	3.949***	7.49***	7.931***	-0.838	2.860***	6.657***	7.495***
t-statistic	(-0.178)	(2.912)	(2.959)	(2.973)	(-0.483)	(2.999)	(3.032)	(3.373)
E. Immigrant Skill Compatibility defined based on 20% threshold								
α	-0.892	3.312**	7.916***	8.808***	-1.307	2.252**	7.091***	8.398***
t-statistic	(-0.365)	(2.471)	(3.122)	(3.21)	(-0.766)	(2.490)	(3.213)	(3.662)
F. Keeping micro-caps								
α	-0.510	3.202**	7.901***	8.411***	-0.961	2.197**	7.029***	7.99***
t-statistic	(-0.215)	(2.382)	(3.153)	(3.399)	(-0.599)	(2.378)	(3.228)	(3.82)
G. Dropping micro-caps based on 20 percentile								
α	-1.205	3.223**	8.171***	9.376***	-1.397	2.178**	7.347***	8.744***
t-statistic	(-0.494)	(2.358)	(3.174)	(3.52)	(-0.834)	(2.343)	(3.249)	(3.899)
H. Dropping financial firms								
α	-0.455	3.249*	7.795***	8.25***	-1.151	2.319*	7.048***	8.199***
t-statistic	(-0.185)	(1.891)	(2.995)	(3.135)	(-0.666)	(1.887)	(3.097)	(3.622)
I. Firms ranked within Fama-French 17 industries								
α	0.060	3.035**	8.697***	8.636***	-0.677	2.259**	7.762***	8.439***
t-statistic	(0.028)	(2.129)	(3.241)	(3.705)	(-0.496)	(2.265)	(3.294)	(3.929)

Table 13: **ImR Portfolio Returns and the Wage Gap between High- and Low- ISC Occupations**

This table reports the relation between the wage gap between high- and low-ISC occupations and the return of the ImR portfolio. The ImR portfolio is defined as the portfolio long firms that belong to industries in the high CLshare quintile and short firms that belong to industries in the low CLshare quintile. Raw ImR represents the settings in which quintile portfolios are constructed across all industries in each year, the Industry-Neutralized ImR represents a setting in which quintile portfolios are constructed within each Fama-French 17 industry, and returns are calculated as the equally-weighted average of the return each quintile across all Fama-French 17 industries. ΔW_t^{emp} is the annual growth in the wage gap between the high-ISC and low-ISC occupations in year t, where wages for each class of occupation is defied as the employment-weighted average of the wages of occupations in that class. The corresponding t-statistics are reported in parenthesis. The last column represents the result of an F-test of whether the sum of the coefficients associated with $R_{ImR,t}$, $R_{ImR,t-1}$, and $R_{ImR,t-2}$ are jointly equal to zero. Significance levels are denoted by * for 1%, ** for 5%, and *** for 10%, respectively.

Dep. Var.: $\Delta log(W_t^{emp})$	$R_{ImR,t}$	$R_{ImR,t-1}$	$R_{ImR,t-2}$	$R_{MKT,t}$	$R_{MKT,t-1}$	$\Delta log(W_{t-1}^{emp})$	F-stat
R_{ImR}	0.012	-0.057***	-0.018	-0.047***	0.006	-0.297	3.028
	(0.663)	(-2.643)	(-1.544)	(-3.224)	(0.356)	(-1.072)	
R_{ImR}^{IN}	0.015	-0.053**	-0.021	-0.038**	0.006	-0.321	1.764
	(0.645)	(-2.121)	(-1.598)	(-2.475)	(0.357)	(-1.107)	

Table 14: **Growth in the Wage Gap as a Proxy for Immigration Policy Shocks**
This table provides estimates of the parameters of the stochastic discount factor $m = a - b_m R_{MKT} - b_w \Delta W$ using the cross-section of Fama-French 30 industries, where ΔW is one of the following proxies for immigration policy shocks: ΔW^{emp} is the annual growth in the gap between the employment-weighted average of the wages of high-ISC and low-ISC occupations; ΔW^{eq} is the annual growth in the gap between the equally-weighted average of the wages of high-ISC and low-ISC occupations; and ΔW^{adj} is the annual growth in the gap between the employment-weighted average of the characteristics-adjusted wages of high-ISC and low-ISC occupations. High-ISC occupations at each year are defined as those that belong to the upper quintile of all occupations in terms of their ISC. The corresponding t-statistics are reported in parenthesis. Significance levels are denoted by * for 1%, ** for 5%, and *** for 10%, respectively.

	(1)	(2)	(3)
R_{MKT}	0.458***	0.452***	0.460***
	(10.241)	(8.652)	(7.476)
ΔW^{emp}	-0.300***		
	(-3.055)		
ΔW^{eq}		-0.242***	
		(-3.606)	
ΔW^{adj}			-0.337***
			(-4.807)
Hansen J-Statistics	5.419	5.431	5.360

Table 15: **Buy American, Hire American: CAR Regression**

This table reports the results of a regression of the firms' cumulative returns (CR) and cumulative abnormal returns (CAR) in the days surrounding the announcement of the "Buy American, Hire American" executive order on their CLshare and its interaction with the firm's unionization. For each firm, CLshare is defined as the share of the firm's total labor costs that are associated with Immigrant Skill Compatible occupations. *Union* is a dummy variable that takes on the value of 1 if the firms belongs to top tercile of industries in terms of labor unionization, and zero otherwise. CAR is obtained by adjusting daily returns over the event window with respect to Fama-French 3 factors, where the factor exposures are estimated based on daily returns over a one-year window ending one month prior to the event date. The t-statistics are reported in parenthesis. Significance levels are denoted by * for 1%, ** for 5%, and *** for 10%, respectively.

	CR		CAR	
	(1)	(2)	(3)	(4)
Event Window: [-1,1]				
CLshare	-0.01***	-0.02***	-0.02***	-0.03***
	(-3.00)	(-4.62)	(-4.22)	(-6.08)
Union		0.00		0.00
		(-0.46)		(-0.39)
CLshare × Union		0.02***		0.03***
		(2.91)		(3.56)
R^2	0.06	0.07	0.07	0.09
Event Window: [-2,2]				
CLshare	-0.02**	-0.03***	-0.03***	-0.05***
	(-2.28)	(-3.79)	(-4.90)	(-6.16)
Union		0.00		0.00
		(-1.25)		(-1.21)
CLshare × Union		0.04***		0.05***
		(3.32)		(3.9)
R^2	0.05	0.06	0.10	0.11
Event Window: [-3,3]				
CLshare	-0.02***	-0.04***	-0.04***	-0.05***
	(-3.28)	(-3.78)	(-5.19)	(-5.62)
Union		0.00		0.00
		(0.33)		(0.10)
CLshare × Union		0.03**		0.03**
		(1.96)		(2.63)
R^2	0.06	0.07	0.06	0.07

Table 16: **Alternative Explanation: Excess Demand**

This table reports the relation between excess demand for employees and expected returns. Panel A reports the value-weighted (equally-weighted) returns and the corresponding alpha of a portfolio that is long industries with the highest Job Openings Rate and short those with the lowest Job Openings Rate, defined as the number of job openings divided by the sum of employment and job openings in the industry. Panel B reports the value-weighted (equally-weighted) returns and the corresponding alpha of a portfolio that is long industries with the highest Layoffs Rate and short those with the lowest Layoff Rate, where Layoffs Rate is defined as the number of layoffs divided by employment in the industry. Unlevered returns are the returns adjusted adjusted for market leverage following Donangelo (2014). Monthly returns are annualized by multiplying with 12, and are presented in percentages. The corresponding t-statistics are reported in parenthesis. Significance levels are denoted by * for 1%, ** for 5%, and *** for 10%, respectively. The sample period covers 1997 to 2016.

Panel A: Sorting with respect to Job Openings Rate

	Levered		Unlevered	
	Hi-Lo (EW)	Hi-Lo (VW)	Hi-Lo (EW)	Hi-Lo (VW)
Raw	-2.38	-3.80	-1.28	-3.03
	(-0.981)	(-1.21)	(-0.54)	(-1.244)
α_{CAPM}	-2.62	-4.35	-1.84	-2.96
	(-1.068)	(-1.377)	(-0.772)	(-1.203)
α_{FF3}	-2.29	-3.55	-1.51	-2.49
	(-0.951)	(-1.167)	(-0.653)	(-1.028)
α_{FF5}	1.16	1.35	2.60	1.02
	(0.483)	(0.452)	(1.165)	(0.425)

Panel B: Sorting with respect to Layoffs Rate

	Levered		Unlevered	
	Hi-Lo (EW)	Hi-Lo (VW)	Hi-Lo (EW)	Hi-Lo (VW)
Raw	-0.22	-2.87	1.25	1.12
	(-0.087)	(-1.075)	(0.678)	(0.534)
α_{CAPM}	-2.09	-2.26	-0.05	0.63
	(-0.886)	(-0.843)	(-0.03)	(0.298)
α_{FF3}	-2.56	-2.86	-0.43	0.16
	(-1.125)	(-1.103)	(-0.262)	(0.076)
α_{FF5}	-2.12	-3.06	-0.18	-0.12
	(-0.884)	(-1.125)	(-0.104)	(-0.054)