PRILIMINARY DRAFT – DO NOT QUOTE

Impact of High Skilled Migration on Publicly Traded US Firms

An Investigation

Anirban Ghosh

5/6/2011

In this paper I analyze the effect of high skilled immigration into the United States on firm productivity, for publicly traded firms. Using individual level data on LCA applications and Permanent Resident Applications, and linking them to US firms; I am able to create a unique dataset that tests the effects of high skilled migration at the firm level. The dataset is very rich with information, but the matching of LCA and Perm data to Compustat had to be done at the employer name basis, and was done manually; and the amount of time required to carry out this exercise was considerable. Moving away from spatial analysis of migration towards the more granular firm level estimation of impacts, I test whether the marginal productivity of the average immigrant is different than the marginal productivity of a native worker. Preliminary results suggest that that under the assumption of perfect substitutes, there is no difference between the marginal productivities of natives and immigrant workers.

Introduction

According to the 2009 American Community Survey, there were 38.5 million foreign-born residents, representing 12.5 percent of the total population[1]. The number and share of immigrants in the US population has been steadily rising over the last few decades. The number of foreign born is estimated to have been 9.6 million (4.7 percent) in 1970, 14.1 million (6.2 percent) in 1980, 19.8 million (7.9 percent) in 1990, and 31.1 million (11.1 percent) in 2000[2]. While there has never been a higher number of foreign born residents living in the United States, as a share, the immigrant population is rivaled only during the turn of the last century when the immigrant shares were estimated to have reached 14.8% in 1890.

Even though the foreign born population in the United States is sizable, they are over represented in the fields of technology, entrepreneurship, education and innovation. 26% of US based Nobel Prize recipients between 1990 and 2000 were immigrants (Peri 2007), 25% of the founders of public venture backed US companies from 1990-2005 were also foreign born (Anderson and Platzer, 2006), as were 25% of founders of new high tech companies in 2006 with at least one million dollars in sales (Wadhwa et. al. 2007). Wadhwa et al (2007) also find that 24% of all parents originating from the United States are authored by non citizens. Borjas (2005) finds that foreign students receive over 50% of all doctorates granted in the field of engineering. Looking at the National Survey of College Students (NSCG, 2003) we see that 22% of immigrants choose to study engineering while only 12% of native college graduates do so.

The above features of over representation and its effects have been studied under the umbrella of the effects of skilled migration into the United States. Benefits of skilled migration have been documented as increasing employment, capital accumulation and income (Ortega and Peri, 2009), or as benefiting the fiscal balance of the welfare state (Boeri, Hanson, and McCormick, 2002; Bonin, Raffaelhueschen and Walliser, 2000). Work on the labor market effects of high skilled immigration has been done by Borjas (2004), focusing on foreign doctorates and their impact on wages[3]. Indeed the impact of immigration has been on wages[4] is probably the most extensively studied question in immigration economics. Chellaraj et al[5]., 2005, estimate the effect of high skilled immigration and on innovation, while Hunt and Gauthier-Loiselle[6], 2008, also looked at immigration's effect on innovation, finding a positive relationship between the number of patents per capita and skilled immigration at the state level. Kerr and Lincoln (2008)

---

[1] Place of birth of the foreign born population 2009, American Community Survey briefs, October 2010. Available at: http://www.census.gov/prod/2010pubs/acsbr09-15.pdf, accessed January 31, 2011.

[2] Gibson, Campbell and Kay Jung. 2006. "Historical Census Statistics on the Foreign-Born Population in the United States: 1850 to 2000." U.S. Census Bureau: Population Division Working Paper, Number 81. Available on the U.S. Census Bureau's Web site at <www.census.gov/population/www/techpap.html>.

[3] George J. Borjas, "The Labor-Market Impact of High-Skill Immigration", The American Economic Review, Vol. 95, No. 2, Papers and Proceedings of the One Hundred Seventeenth Annual Meeting of the American Economic Association, Philadelphia, PA, January 7-9, 2005 (May, 2005), pp. 56-60

[4] Linda Levine (2010), "Immigration: The Effects on Low-Skilled and High-Skilled Native-Born Workers" provides an extensive survey. Available at: http://fpc.state.gov/documents/organization/142751.pdf

[5] Gnanaraj Chellaraj, Keith E. Maskus, and Aaditya Mattoo, "The Contribution of International Graduate Students to US Innovation", Review of International Economics, Vol. 16, Issue 3, pp. 444-462, August 2008.

[6] Jennifer Hunt, and Marjolaine Gauthier-Loiselle, "How Much Does Immigration Boost Innovation?" Available at: http://www.mcgill.ca/files/economics/howmuchdoes.pdf

find a positive effect of the number of H1B visas granted to the direct contribution of ethnic innovators. A related paper by Peri and Sparber[7] look at the effect of high skill immigration on occupational choice of natives with graduate degrees. Peri and Sparber find that those occupations where immigrants have entered in disproportionately larger numbers, natives have moved towards tasks that require less quantitative and more management skills[8].

One area which has not received attention has been the effect of skilled migration on the productivity of US firms. From both Kerr and Lincoln (2008) and Hunt and Gauthier-Loiselle (2008) we can expect that if there indeed is a causal effect of immigration on innovation, we ought to expect a similar relationship between skilled migration and productivity. This is because innovation and technological improvement increases efficiency with which inputs are converted into outputs in an economy. However, formal testing for this link is not extensive in literature.

This paper tests directly the effect of employing high skilled immigrants on productivity of publicly traded firms in the United States. In particular, we test whether high skilled immigrants who are employed via H1-b visas and work sponsored Permanent Resident certifications boost productivity of publicly traded firms in the United States between 2000 and 2006.

Theory – why should there be a relationship between skilled migration and productivity

There are many channels through which one expects a relationship between firm productivity and skilled migration. Comin (2008)[9] identifies four channels through which total factor productivity of a firm can be influenced. These are R&D spending and innovations, abundance of skilled labor, changes in size of markets, Tax Policy and labor market regulations. Skilled migrants affect the second of these channels (abundance of skilled labor) most directly, and Kerr et. al. (2008) and Hunt et al (2008) both investigate the innovations channel.

Rivera-Batiz and Romer (1991) show in endogenous growth models that sharing of ideas across countries can lead to higher levels of innovation. From international trade literature (for example Coe, Helpman, and Hoffmaister (2008) and MacGarivie, (2006) we see empirical evidence that imports from one country provide a method of transferring technology between countries. One may consider skilled migrants as a variant of imports, instead of importing the final goods, one imports the factor of production. Thus, one can think of high skilled immigrants as another channel through which information, ideas and R&D from one country can be transferred to another country.

Other possible channels through which immigration can affect productivity can be a selection effect, which if positive suggests that immigrants are more hard working than natives. However,

[7] Giovanni Peri, Chad Sparber, "Highly-Educated Immigrants and Native Occupational Choice", 2008

[8] "We find that immigrants with graduate degrees specialize in occupations demanding quantitative and analytical skills, whereas their native-born counterparts specialize in occupations requiring interactive and communication skills. Native employees leave occupations with a high proportion of highly educated immigrants for occupations with less analytical and more communicative content." Peri/Sparber 2008 Abstract

[9] Comin, Diego. "Total Factor Productivity." *The New Palgrave Dictionary of Economics*. 2nd ed. Edited by Steven Durlauf and Lawrence Blume. Palgrave Macmillan, 2008. Available at: http://www.people.hbs.edu/dcomin/def.pdf

we might even see a negative effect which might mean that it takes immigrants time to assimilate and be as productive as natives. This would suggest a labor market where skilled natives are unavailable for this particular job opening, and immigrants are a second best alternative.

The purpose of this paper is not to explore which of these channels are dominant, but as a first step, to directly measure, at the firm level, whether skilled immigrants affect productivity. Moreover, since the effect can be either positive or negative, measuring this effect is a necessary first step towards better understanding the labor market effects of skilled immigration.

Current Literature on Productivity

In the current literature, the effect of immigration on productivity is analyzed in two methods. The first is the spatial analysis method, which takes advantage of heterogeneous geographic distribution of immigrants in a given country, and the differences in the immigration concentration are the n correlated with geographic differences in productivity. This method of analysis was first introduced by David Card (2001[10]), and has been used to measure the effect of immigration on wages and occupational distribution (Peri and Ottaviano, 2008[11]). In any of these spatial analysis papers, the typical unit of measurement is a certain geographic region. For the United States, this is typically an MSA or a state. Two papers that look at productivity and immigration following this methodology are Quispe-Agnoli and Zavodny (2002[12]) and Peri (2009[13]). Both these papers use the state as the unit of measurement, and calculate the changes in the productivity of the state in producing goods as the unit of measurement. The papers also assume that all immigrants are alike, as a representative immigrant. Peri (2009) finds that within these constraints, where immigrants are homogenous, immigrants have a positive effect on productivity. Quispe-Agnoli and Zavodny too finds a similar result, again with the state as a unit of measurement, and homogeneous immigrants. In addition to the analysis being done at the aggregate level, the assumption of all immigrants being treated the same biases the measure towards analyzing unskilled migration, since in the United States, they form the majority of immigration.

A second and more straight forward method of measuring the effect of immigration on firm productivity is by directly measuring firm productivity by using the firm as the unit of measurement, i.e. looking at the firm's data on profits, sales, and immigrants. This is the most direct method of measuring the effect in question, and while using the special arguments

---

[10] "Immigrant Inflows, Native Outflows and the Local Labor Market Impacts of Higher Immigration." Journal of Labor Economics 19 (January 2001).

[11] Peri and Ottaviano **, 2008. Highly-Educated Immigrants and Native Occupational Choice. Available at: http://ideas.repec.org/p/crm/wpaper/0813.html**

[12] MYRIAM *QUISPE-AGNOLI* AND MADELINE *ZAVODNY (2002). "*The *Effect of Immigration* on *Output Mix*, *Capital*, and *Productivity*." Economic Review, Federal Reserve Bank of Atlanta, first Quarter 2002. Available at: http://www.frbatlanta.org/filelegacydocs/quispe_zavodny.pdf

[13] Giovanni Peri, 2009. "The Effect of Immigration on Producvitiy: Evidence from the US States" NBER Working Paper Series, Working Paper 15507. Available at: www.nber.org/papers/w15507

forwarded by Peri and Quispe-Agnoli can take into account some spillover effects, the direct measurement is less vulnerable to other omitted variable problems. An example of such a paper is Paserman (2008)[14] which uses firm level data to analyze the effect of a large immigration push into Israel during the last decade of the previous century on firm productivity. Paserman's paper finds the effect of high skilled immigration is negative on productivity.

A third method which has been used is a fusion of these two, where the firm level profitability data is merged with city level immigration statistics. An example of such a paper is Carrizosa and Blasco (2009)[15] which analyzes the effect of immigration into Spain. However, even through the firm level data is used in this paper, since the immigration statistics are measured at the city level, identification is still at the city, i.e. aggregate level.

My Paper

One of the reasons why immigration analysis has been restricted to using aggregate data and spatial analysis thus far, especially for the united states, is that there is no specific dataset that links immigrants to firms. In this paper, I create a unique dataset that matches new labor condition certificates (first step towards H1-b) and work authorized permanent resident authorization to an employer. This is the first time such a dataset has been created, and is unique to this project. Through this dataset, for each publicly traded firm in the United States, I am able to identify the number of LCA and Permanent Resident applications that were made by year, and the salaries that are offered, in addition to further information such as whether the application was certified or denied. This information can then be linked to the firm specific information available at Compustat Industrial Annual data. Examples of information available are sales, number of employees, cost of employees, retained investment, cost of plant, equipment and machines, cost of labor, and other stock price related information.

The dataset is very rich with information, but the matching of LCA and Perm data to Compustat had to be done at the employer name basis, and was done manually; and the amount of time required to carry out this exercise was considerable. The reason why the matching was tedious is because the Employer name in the LCA and PERM database are not standard, so the first step was to identify all the different ways in which a single firm's name can be written (Microsoft, Microsoft Corp, Microsft Corp, Microsoft Corporation) along with any spelling errors of the names, and then as the second step match these firms to the Compustat data[16].

My contributions through this paper are the following:

- First paper to directly measure the impact of immigration on firm productivity in the United States.
    - Paserman's results are not generalizable to the US, since a lot of immigrants came to Israel while fleeing the Soviet Union, and hence there was an immigration

[14] M. Daniele Paserman (June 2008). "Do High-Skill Immigrants Raise Productivity? Evidence from Israeli Manufacturing Firms, 1990-1999." Available at http://ftp.iza.org/dp3572.pdf

[15] Mercedes Carrizosa and Agusti Blasco, (2009). "Immigration and Firm Performance: a city level approach." Investigaciones Regionales Monografico – Paginas 111 a 137.

[16] I describe the data cleaning process in more detail in the appendix

push. In the US, with LCA and PERM data, the firms actually demand these workers. Thus we are analyzing a different dynamic.
    - Peri and previous papers did not measure the impact directly at the firm level but, rather, relied on aggregate data.
- First paper for the US to measure high skilled immigrants' impact on productivity
    - Both Peri and Quispe-Agnoli consider immigrants as a homogeneous. Since the US immigrants are majority unskilled, this invariably leads to analysis of unskilled immigration's effect on productivity. Both LCA and PERM applicants are mainly high skilled, and this is the first time we are able to measure high skilled worker productivity directly.
- Why do this paper?
    - All the spatial analysis papers have seen positive effects of immigration on productivity. Moreover, from the theory discussion earlier, we expect to see a positive effect of skilled migration on productivity. However, the only other paper on high skilled migration has showed the effect to be negative. I do not expect Paserman's results to carry over, but since the effect has not been estimated as positive consistently, there is a need for study in this area. Moreover, a direct measurement of firm level productivity is much more rigorous than spatial analysis.

The Data

For this paper, I have created a unique dataset combining three separate data sources:

- The Permanent Labor Certification Data (PERM)
- The Labor Condition Certification Data (LCA)
- Compustat data for publicly traded firms

The following paragraphs introduce each of the three data sources and also describes the matching process.

The Permanent Labor Certification (PERM) Data

The data listed in http://www.flcdatacenter.com/CasePerm.aspx are the case records of permanent labor certification issued by the Department of Labor (DOL). The labor certification is the first step towards hiring an alien on an indefinite basis for the given firm. The application is filed by the employer using the form Permanent Employment Certification, ETA Form 9089[17]. The steps towards permanent residence where the employer must prove that they cannot find a US citizen to do this job, and also prove that they are employing the alien at the prevailing wage[18].

---

[17] http://www.antaoandchuang.com/en/labor-certification/what-forms-or-documents-must-employer-include-application
http://www.foreignlaborcert.doleta.gov/perm.cfm

[18] The immigrant petition process is as follows:

1. Immigrant Petition

In this analysis we will be using data from 2000 – 2007[19]. The data for each year is for the fiscal year, i.e. from October of the previous year through September of that year, of when the application decision was reached.

For all year, we have the status of the application, the employer name and address and detailed information on the offered wage, occupational title and the prevailing wage of the occupation. We will be using the employer name and address and the status of the application as our main sources of data as we match applicants to firms. For data from 2000 through 2004, we are also given the names of the attorneys who are handling the case, while between 2005-2007, we have data on the citizenship of the applicants.

Below in Table 1, I give you the number of PERM applications by year, and by whether they were certified or not.

Table 1 – The total number of PERM applications between 2000 and 2007[20]

year	certified	Not Certified	Total	% Certified
2000	70098	3817	73915	95%
2001	77758	4201	81959	95%
2002	79670	9337	89007	90%
2003	62848	32191	95039	66%
2004	43498	54804	98302	44%
2005	6128	7951	14079	44%
2006	79687	25967	105654	75%
2007	84430	12831	97261	87%
Total	504117	151099	655216	

The Labor Certification Data (LCA data)

The data that is available online is the Labor Condition Application (LCA) data. This is the first step towards applying for an H1-B visa. The LCA is applied with the Department of Labor,

---

1. Labor Certification by Department of Labor – the employer must prove that they cannot find a US citizen to do this job, and also prove that they are employing the alien at the prevailing wage.
2. Immigrant Petition – After the labor certification, the employer can apply for a visa number through the I-140, Immigrant Petition for Alien Worker form.

2. Immigrant Visa Availability – The visa is made available based on the Priority Date, (which is the date when the labor certification was applied), that the Department of State is currenty processing.
3. Adjustment of Status and Counsular Processing

[19] Data through 2010 recently became publicly available, but was not used during the consolidation process for this paper

[20] You will notice that 2005 the total number of applications were much smaller than other years. In March, 2005, a completely electronic labor certification system, PERM (Program Electronic Review Management) came into use. This is different from previous methods. PERM is intended to reduce labor certification times to under 60 days, although due to backlogs this aim is still to be realized . Given that the DOL was changing its system in 2005 also probably explains why there are so few records released in 2005.

whose function is to ascertain that the hiring of the foreign worker does not displace or adversely affect wages or working conditions of U.S. workers.

The H1-b visa is typically a 3 year visa which can be renewed for a second three year term. For both first time applications as well as renewals we need to file an LCA application. The data available via http://www.flcdatacenter.com/CaseH1B.aspx does not distinguish between the two types of applicants.

The certification process by the Department of Labor only checks for obvious errors. This is one of the reasons that typical LCA's are typically certified. For example, in the 2008 e-file data, out of 405,651 applications, 404,422 were certified and only 1,229 were denied:

> The Secretary of Labor shall review such an application only for completeness and obvious inaccuracies. Unless the Secretary finds that the application is incomplete or obviously inaccurate, the Secretary shall provide the certification described in section 1101 (a)(15)(H)(i)(b) of this title within 7 days of the date of the filing of the application[21].

LCA can be filed both by fax and e-file. The data includes 2001 Fax filings, 2002 – 2006 both e-file and fax data, and 2007 – 2008 e-file data. The e-file option was available starting in 2002, and by 2004, 90% of the LCAs were filed until the e-filing system. Thus, the available data is 100% of the LCAs for years 2001 – 2006 and at least 90% of the LCAs for 2007 and 2008. In 2004, the numbers of e-file cases were 308,710. Below in table 2 I give you the number of LCA application by certification status and also by whether they were filed via fax or email. In my analysis I treat both fax and email to be equivalent measures of filing an LCA.

Table 2 – LCA Applications by certification status, and whether received by email or fax

year	Not Certified	Certified	Total	Percent Certified	email	fax	Total
2001	42,742	244,388	287,130	85.1%	0	287,130	287,130
2002	20,269	248,500	268,769	92.5%	122,774	145,995	268,769
2003	8,331	259,623	267,954	96.9%	220,927	47,027	267,954
2004	7,189	332,337	339,526	97.9%	308,352	31,174	339,526
2005	3,102	314,122	317,224	99.0%	307,381	9,843	317,224
2006	8,088	377,147	385,235	97.9%	383,499	1,736	385,235
2007	2,159	389,698	391,857	99.4%	391,857	0	391,857
2008	720	342,094	342,814	99.8%	342,814	0	342,814
Total	92,600	2,507,909	2,600,509	96.4%	2,077,604	522,905	2,600,509

Each LCA application has a case number, employer's name and address, occupation code, wage rate, prevailing wage and also an indicator of the source of the prevailing wage.

[21] http://www.law.cornell.edu/uscode/html/uscode08/usc_sec_08_00001182----000-.html

Not every labor condition application will result in an H1B visa. Every year, there is a cap on the number of visas that are granted by the US. Some institutions, such as universities are exempt from this H1b cap, and also some countries such as Chile have their own quotas which do not fall under the cap. The H1b cap imposed by the congress was 115,000 in 2000, 195,000 in 2001 through 2003, and then 65,000 in 2004, and beyond[22]. These quotas were not binding until 2004. In 2004 and 2005, the visas were reviewed on a first come first served basis, and then from 2006 onwards the visa petitions were reviewed by lottery.

Building the dataset

A major effort for this paper has been in creating the dataset that I will be using. As mentioned previously, each of the applications have the employer name and address. The main problem with the data is that the name of the employer is not consistent across applications. An example of this are "AGFIRST FARM CREDIT BANK" and "AGFIRST FCB". The method used to recognize whether an employer is the same was iterative and there was a lot of visual inspections involved. The outline of the methodology is given below:

1. First using only the PERM dataset, the employers whose named seemed to be similar and were from the same city were considered to be the same.
2. Next I focused on those employers whose names were similar enough, but were from different cities. I used a wordmatch software, which gives me a percentage match between two words. I determined that if two employer names were more than a 75% match, they were likely to be the same employers. This is not foolproof, but considering different thresholds, this seemed to work best[23].

Percentage match with the entry directly above	
BATON ROUGE INTERNATIONAL	N/A
BATON ROUGE INTERNATIONAL INC	86%
BATON ROUGE INTERNATIONAL INC.	97%
BATON ROUGE INTERNATIONAL, INC.	97%
BATON ROUGE INTERNATIONAL,INC.	97%
BATTELLE	0%
Battelle Memorial Institute	0%
BAXTER HEALTHCARE CORP	26%

[22] Page 2, Kato and Sparber, "Quotas and Quantity: The effect of H1B Visa Restrictions on the Rool of Prospective Undergraduate Students from Abroad.

[23] [23] It was first written by Anonymous, 2006 as an ad-on to the excel suit and is made publicly available on the web site: http://hairyears.livejournal.com/115867.html#NormaliseAddress

Previous users have also cited the following:
Anonymous. (2006). "Fuzzy matching - new version plus explanation Pseudonym: al_b_cnu]." Manchester, MrExcel.com Retrieved 10 Jun 2008, from http://www.mrexcel.com/forum/showthread.php?p=955137.

3. There were 2015 employers which had over 75% matching names but different names, and I went through each of these to manually determine if they were the same employer or not. They usually turned out to be the same employer.
4. I went through the top 200 highest employers, and manually checked if they can be consolidated as well.
5. Once I had determined which employer names were the same firm, I then assigned a unique identifier for each firm. There were a total of 297,134 employer-city combinations in the PERM dataset.

A similar process was done for the LCA dataset, with the additional constraint that I had to make sure that if the firm was already identified in the PERM dataset, then I had to assign it the same unique identifier as the PERM dataset. The number of unique employer name-city combinations was larger, at 890,933 combinations. Here too the largest 200 employers were manually updated to make sure that they are all correctly assigned.

Thus at this stage, I was able to create a dataset that identifies unique firms that have applied for both LCA certifications and Permanent Resident Certifications. At this point we can summarize at the firm level, how firms behave when applying for LCA and Permanent Resident visas.

Table 3 – Decile Analysis of LCA for years 2001-2008. This table shows the concentration of the LCA applications amongst certain firms.

decile	Decile Definition = number of LCA Applications	Number of Firms	Number of LCA Applications	Cumulative Number of Firms	Cumulative Number of LCA Applications	% of firms	% of LCA applications	Average LCA applications per firm
10	more than 1000	184	461109	184	461109	0.1%	18%	2,506.03
9	501 to 1000	280	194209	464	655318	0.1%	25%	693.60
8	201 to 500	972	297198	1436	952516	0.4%	37%	305.76
7	101 to 200	1522	213891	2958	1166407	0.8%	45%	140.53
6	51 to 100	2843	198673	5801	1365080	1.7%	52%	69.88
5	21 to 50	8261	256258	14062	1621338	4.0%	62%	31.02
4	11 to 20	14085	202223	28147	1823561	8.0%	70%	14.36
3	6 to 10	29508	219560	57655	2043121	16.5%	79%	7.44
2	2 to 5	142124	407402	199779	2450523	57.1%	94%	2.87
1	1	149986	149986	349765	2600509	100.0%	100%	1.00

Notice that 1% of the firms account for about 50% of the LCA applications. This concentration is reflected in the figure below as well.

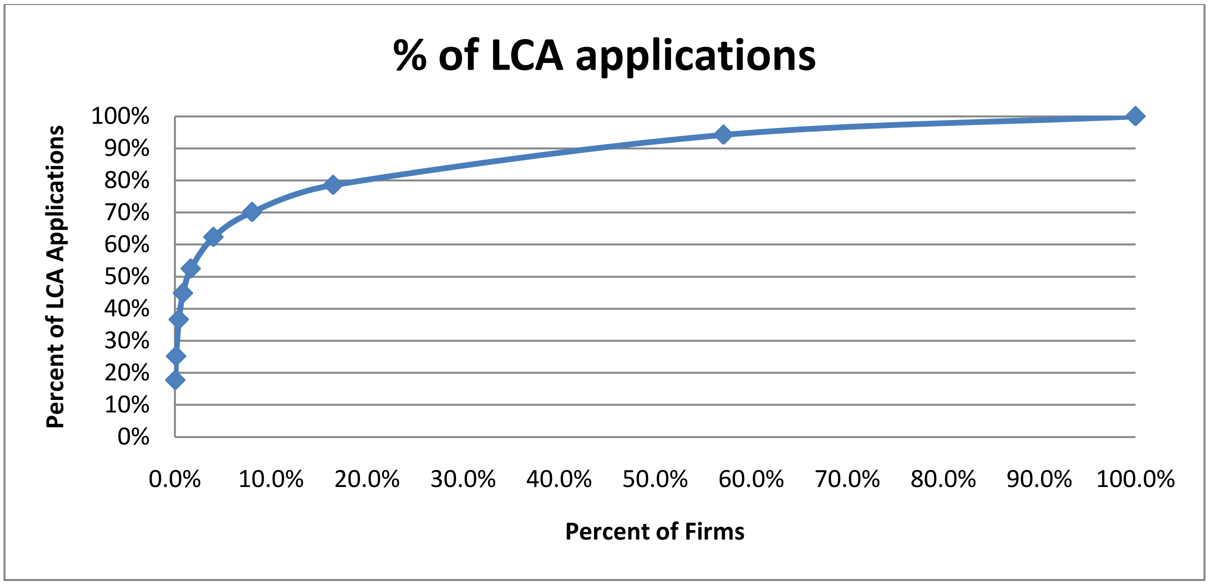

Figure 1 – the share of firms and the share of LCA applications.

Observe that there are nearly 400 firms which have applied for at least 500 LCA visas during our sample period. Out of these, the top decile of 184 firms have applied for at least 1000 visas between 2001 and 2008. The firms that apply for LCA applications is very concentrated into a few firms, and there is also a huge number of firms, nearly 150,000 which have applied for only 1 LCA application!

Table 4 – PERM decile analysis for years 2000-2007. I used the same definitions for deciles on both the PERM and the LCA data.

decile	Decile Definition = number of PERM Applications	Number of Firms	Number of PERM Applications	Cummulative Number of Firms	Cummulative Number of PERM Applications	% of firms	% of PERM applications	Average PERM applications per firm
10	more than 1000	12	24425	12	24425	0.0%	4%	2,035.42
9	501 to 1000	30	20505	42	44930	0.0%	7%	683.50
8	201 to 500	91	27002	133	71932	0.1%	11%	296.73
7	101 to 200	246	33918	379	105850	0.2%	16%	137.88
6	51 to 100	555	38552	934	144402	0.4%	22%	69.46
5	21 to 50	1915	58923	2849	203325	1.3%	32%	

								30.77
4	11 to 20	3492	49605	6341	252930	2.8%	39%	14.21
3	6 to 10	7995	59198	14336	312128	6.3%	49%	7.40
2	2 to 5	65332	172544	79668	484672	35.0%	76%	2.64
1	1	147781	157218	227449	641890	100.0%	100%	1.06

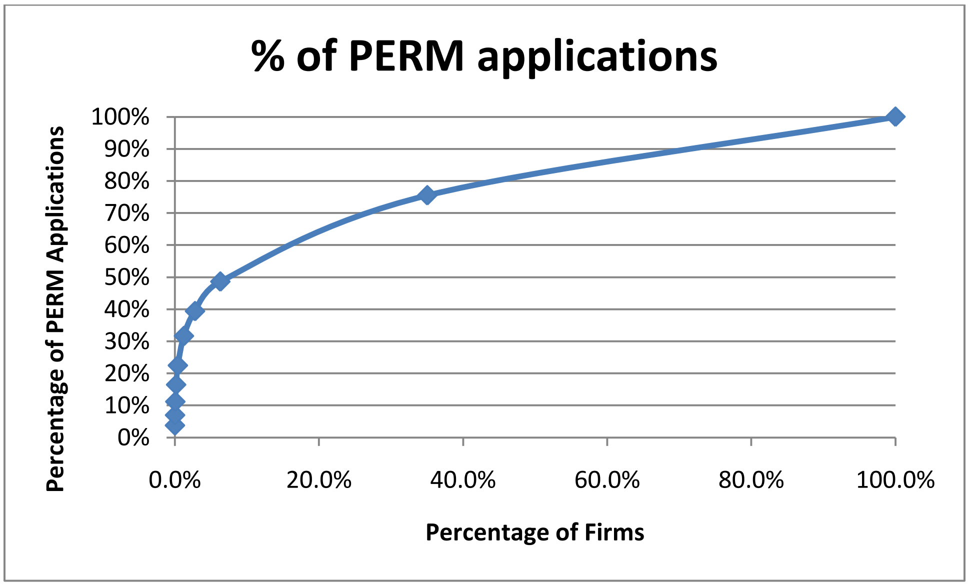

Figure 2 – The concentration of PERM applications by the number of firms.

This is not as concentrated as LCA data, but still 6.3% of firms account for about 50% of all PERM applications. There are also a lot fewer permanent resident applications than LCA applications. For example, only 12 firms have applied for more than 1000 permanent applications during our sample period.

The next and final step in this process is to match these firms with the Compustat data. Compustat data is all publicly traded firms' balance sheet data, and for the years 2000 through 2006, there are a total of 22,633 firms. Unlike the manufacturing census data, the Compustat is publicly available. A very similar process of matching the employers by name is done to match the LCA and PERM dataset to the Compustat dataset. At this matching stage, there was further manual matching done, especially for the higher decile employers. For example, all firms in deciles 9 and 10, I inspected manually to make sure that they are not missed in the Compustat data. The reason for additional checking here was because Compustat data is for publicly traded firms, and they are likely to be bigger, and hence probably more likely to apply for either an H1b or a Permanent Resident visa.

The entire process identified a total of 3,548 firms which had applied for at least one employer based permanent resident application (PERM), and 5,279 firms which have applied for at least one Labor Condition Certification Application (LCA) that have been matched with the Compustat database of firms. This is the only place I am aware of where such a dataset has been created. The data cleaning and matching process has been very extensive, and I have also compared the numbers of LCA applications for the top employers with other independent sources, and for these top employers, my data has similar numbers as other data. All other sources that has been published only look at the top firms (for example the top 100), so I cannot compare my data for the lower number of LCA and PER M applications. However, the extensive cleaning of this dataset gives me enormous confidence in using this dataset for analysis.

Below in tables 5 and 6, I compare the firms that apply for LCA and PERM with those that I matched with Compustat data. Notice that in both cases, the bigger employers, i.e. higher deciles, were usually also found in the Compustat database. Some larger employers of immigrant labor cannot be identified in this data, because these firms are not publicly traded firms, such as Ernst and Young or Deloitte consulting, both of which are partnerships. A second major course of immigrant labor hires are Universities, which are also excluded from the Compustat database.

Table 5 – Compares the matched firms with all firms for LCA applications.

decile	Decile Definition = number of LCA Applications	Number of Firms Applying	Number of Firms Matched to Compustat	Percentage of Firms Matched	Number of LCA Applications	Number of LCA Applications Matched to Compustat	% of LCA Applications Matched
10	more than 1000	184	73	40%	461109	223786	49%
9	501 to 1000	280	71	25%	194209	49447	25%
8	201 to 500	972	95	10%	297198	29579	10%
7	101 to 200	1522	168	11%	213891	24136	11%
6	51 to 100	2843	285	10%	198673	19787	10%
5	21 to 50	8261	540	7%	256258	17416	7%
4	11 to 20	14085	612	4%	202223	8978	4%
3	6 to 10	29508	720	2%	219560	5479	2%
2	2 to 5	142124	1696	1%	407402	5347	1%
1	1	149986	1019	1%	149986	1019	1%

Table 6 – Perm application firms matched to Compustat data. There are a total of 3548 firms that are matched with my data.

decile	Decile Definition = number of PERM Applications	Number of Firms	Number of PERM Applications	Cummulative Number of Firms	Cummulative Number of PERM Applications	% of firms	% of PERM applications	Average PERM applications per firm
10	more than 1000	10	21721	10	21721	0.3%	26%	2,172.10
9	501 to 1000	18	11356	28	33077	0.8%	39%	630.89
8	201 to 500	53	16208	81	49285	2.3%	59%	305.81
7	101 to 200	62	8932	143	58217	4.0%	69%	144.06
6	51 to 100	105	7594	248	65811	7.0%	78%	72.32
5	21 to 50	213	6861	461	72672	13.0%	86%	32.21
4	11 to 20	273	3969	734	76641	20.7%	91%	14.54
3	6 to 10	364	2772	1098	79413	30.9%	94%	7.62
2	2 to 5	1198	3476	2296	82889	64.7%	99%	2.90
1	1	1252	1252	3548	84141	100.0%	100%	1.00

Theory

The question that I am interested in answering with this data is whether immigrants are more productive than natives. Note that immigrants who are either H1B or Employer Sponsored Green Card, are high skilled as a requirement for getting this visa.

Following Paserman (2008), I assume that immigrants and natives are perfect substitutes, but they may have different marginal productivities. I use a standard Cobb-Douglas production function, where output (Y) is a function of capital (K), labor (L), materials (M), and technology (A). Then the firm's production function takes the form: $Y = AK^{\alpha} M^{\beta} L^{\gamma}$

Then define Labor = Native + Immigrants (h1b) + immigrants (Permanent residents)

$L = Ln + Lh1 + Lp$

And define s1 and s2 such that $Lh1 = s1*L$ and $Lp = s2*L$. Thus, $Ln = (1\text{-}s1 - s2)L$

Recall our assumption that natives and the two types of immigrants are perfectly substitutable but their marginal productivities can be different. Specifically if μ is the difference in productivity between H1b immigrant and native, and σ is the difference in productivity between Permanent Resident and native, we can write the following production function:

$Y = AK^{\alpha} M^{\beta} [Ln + (1+\mu)Lh1 + (1+ \sigma)Lp]^{\gamma}$

The substituting in the labor ratios (i.e. s1, s2 etc) and simplifying we get the equation:

$Y = AK^{\alpha} M^{\beta} L^{\gamma} [1 + \mu*s1 + \sigma*s2]^{\gamma}$

Taking logs and using the approximation $\log(1 + \mu*s1 + \sigma*s2) = \mu*s1 + \sigma*s2$, we get:

$\mathrm{Log}(Y) = \log(A) + \alpha\log(K) + \beta\log(M) + \gamma \log(L) + \gamma \mu*s1 + \gamma \sigma*s2$

The last addition that we make in this model is that we assume that we let each firm have an idiosyncratic effect, and thus, the model to estimate becomes:

$\mathrm{Log}(Y_{it}) = \log(A_{it}) + \alpha\log(K_{it}) + \beta\log(M_{it}) + \gamma \log(L_{it}) + \gamma \mu*s1_{it} + \gamma \sigma*s2_{it} + a_i + \epsilon_{it}$

This equation can then be estimated in the first difference form:

where A_{it} is replaced by a set of controls, $X\beta$.

$\Delta\mathrm{Log}(Y_{it}) = \Delta\log(A_{it}) + \alpha\Delta\log(K_{it}) + \beta\Delta\log(M_{it}) + \gamma\Delta \log(L_{it}) + \gamma \mu\Delta s1_{it} + \gamma \sigma\Delta s2_{it} + \epsilon_{it}$

where $\Delta s1_{it}$ and $\Delta s2_{it}$ are estimated by the following ratios:

$\Delta s1_{it}$ = # of LCA Applications $_{it}$/ # L_{it}

$\Delta s2_{it}$ = # of PERM Applications $_{it}$/ L_{it}

There are two reasons why first differences are used in this estimation. First, we have the data on the number of new LCA applications, and new PERM applications, but we do not know the stock of immigrants in a firm, but we do know the flow of new immigrants each year. Secondly, estimating in first differences may lead the coefficients to have a causal interpretation if any non-randomness of a firms decision to hire immigrants stayed constant over the sample period, and thus were differenced away.

Results

The Determinants of LCA and PERM applications

As a first step, I wanted to find the determinants or the characteristics of firms that hire immigrants. I look at both the LCA applications and the Permanent Labor Certifications (PERM) separately. I regress the number of LCA applications or PERM applications on a number of firm specific characteristics, which include, the number of employees and its squared value, Research and Development expenses, a dummy as to whether a firm does any R&D, capital over labor ratio, the output share of the firm in either the 2 digit naics industry definition or the 3 digit. Additionally, in some specifications, the number of employees variable is split up into dummy variables proxying for firm size; a dummy for whether the firm is in a high tech industry, and state, industry and firm fixed effects are added. Since there are a lot of firms which have zero number of immigrants, the appropriate model is a tobit regression model. I also use robust standard errors to control for heteroskedasticity, and in the models where I have fixed effects, I cluster around the fixed effect.

Table 7a shows the results for LCA Applications and Table7b shows the PERM applications. Please also note that from this point on, all the tables are at the end of the paper.

From Table 7a, we see that there is clearly a firm size effect, where larger firms file for more LCA applications. LCA applications are also positively and significantly correlated with Research and Development expenses and also whether a firm engages in R&D at all. Additionally, the higher the output share of a firm within an industry, they file for more LCA applications. LCA applications is also sector specific, as more visas are filed if the firm is in a high tech sector. The capital to labor ratio is negative and significant for some specifications, suggesting that perhaps LCA applications are correlated with more labor intensive firms, but these effects disappear when we account for firm size dummies, and industry fixed effects. The annual wage offered to an LCA applicant is also negatively correlated with the number of LCA applications by the firm.

In Table 7b, we see the determinants of PERM applications. The determinants are very similar to the LCA applications. As with table 7a, we see that there is clearly a firm size effect, where larger firms file for more PERM applications. PERM applications are also positively and significantly correlated with Research and Development expenses and also whether a firm engages in R&D at all. Additionally, the higher the output share of a firm within an industry, they file for more PERM applications. PERM applications is also sector specific, as more visas are filed if the firm is in a high tech sector. Unlike the LCA applications, the capital to labor ratio is never significant, and the average annual wage offered to a PERM applicant is also not significant.

Estimation of the Production Function

We now move on to the estimation of the production function. First we estimate a baseline production function, where output is a function of labor, capital, materials and some technology shifters, namely R&D expenses, assets and investments. The production function that we are estimating takes the following form:

$Y = AK^{\alpha}M^{\beta}L^{\gamma}$

Some details of each of the variables and how they were calculated are in order:

1. Y = output. We use Net Sales as the measure of output. This is data12 in Compustat data. Net Sales is defined as gross sales (the amount of actual billings to customers for regular sales completed during the period) reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers.

2. A = technology shifters. We estimate technology shifters by the Research and Development expenses. This is data46 in the Compustat data and represents all costs that relate to the development of new products or services.

3. L = labor. We measure labor as the number of employees.

4. M = materials. This measure is constructed using the following definition: Materials = Cost of Goods Sold + Administrative expenses – depreciation – wage expenses. I follow Keller and Yeaple (2004) to construct this estimate. While Cost of Good Sold (data41), Selling, General, and Administrative Expense (Xsga), and depreciation (data14) are available in Compustat data, I had to create the labor expenses variable separately. For manufacturing firms until 2005, I used Bartelsman and Grey's estimates of average wage at the naics and sic levels[24]. For non-manufacturing firms, and for 2006, I used the BLS national average occupational wages, which also gives the NAICS industrial level average wage per employee[25]. Note that in Compustat, for some firms that are more diversified, the NAICS code is not at the 6 digit level, but can be at the 4 or 3 or even 2 digit levels. For each of these measures, I first matched each firm at the naics 6 digit level, then at the 4 digit level, 3 digit, and so forth, i.e. hirarchchically towards each more disaggregated level. I use this industry measure of average employee wage, multiplied by the number of employees as the labor expense estimate.

5. Capital expenses (**CAPX)** has been used as a proxy for investments by some authors. I use this in some specifications as a technology shifter. This is the funds used for additions to property, plant, and equipment, excluding amounts arising from acquisitions.

6. K = Capital is measured as Property, Plant, and Equipment – Total (Net) (data8) in Compustat. This is the cost, of tangible fixed property used in the production of revenue, less accumulated depreciation.

The equations are estimated in log form. From Table 10 a and b, the two baseline models, we see evidence that the standard production function estimation is reasonable. Capital, Labor, and Materials are significant and positive for all specifications, including the model 7, where we introduce firm level fixed effects. Investment is positive and significant except in the model with firm level fixed effects which suggest that investment decisions tend to be firm specific. High tech firms have slightly higher output. Do note that high tech firms are defined at the 4 digit naics levels, and so even though we use 2 and 3 digit industry fixed effects, it does not make the high-tech dummy variable redundant. The difference between the two baseline models is that in the second baseline model, I introduce the variable for capital investment. The parameter estimates for all other variables is stable to the inclusion or exclusion of this variable. Research and Development has a negative coefficient, and this is understandable since money spend on R&D is presumably money taken away from making current output that can be sold in the present time. R&D expense is likely to be an indicator of future growth of the firm, and hence is not surprising that the coefficient is negative.

---

[24] Available at: http://www.nber.org/data/nbprod2005.html

[25] http://www.bls.gov/oes/oes_dl.htm

Table 10a and 10b establish the baseline results for the estimated parameters for a standard production function. The very high R-squared values indicate that we are able to capture most of the variation in output.

Recall from the previous section that the main objective is to estimate the following model:

$\Delta Log(Y_{it}) = \Delta log(A_{it}) + \alpha\Delta log(K_{it}) + \beta\Delta log(M_{it}) + \gamma\Delta log(L_{it}) + \gamma\mu\Delta s1_{it} + \gamma\sigma\Delta s2_{it} + \epsilon_{it}$

At this point, note that $\Delta s1_{it}$ and $\Delta s2_{it}$ are estimated by the following ratios:

$\Delta s1_{it}$ = # of LCA Applications $_{it}$/ # L_{it}

$\Delta s2_{it}$ = # of PERM Applications $_{it}$/ L_{it}

And where A_{it} is replaced by a set of controls, $X\beta$. Also, I want to point out that the change is share is only approximated by the above ratios, but this approximation is fine since the ratio (L_{it} - L_{it-1})/ (L_{it} * L_{it-1}) is small enough. The above equation is estimated in tables 9a and 9b.

Interpreting table 9a, we see the major elements of the model are consistent with the baseline results. Labor , capital and materials are still positive and significant in all of the models. Research and development expenses are still negative for most of the specifications. High tech is no longer significant, but that is not unexpected since we are estimating in first differences. This model does not lend any support to the argument that immigrants are more productive than natives, as both the shares of LCA and PERM are insignificant.

In table 9b, the specifications are the as for 9a, except we also add in the capital investments variable. Both investments and capital are not significant. Labor and materials are still positive and significant, and research and development expenses, unsurprisingly are still negative. Both the shares of LCA and PERM are not significant except in one specification where LCA applications are negative and significant.

These results are interesting, since hiring immigrants is costlier than hiring native, in terms of lawyer fees etc., and also since presumably there is a labor shortage which foreign labor rectifies. One area of concern is that not all LCA applications are automatically converted into H1B visas. There is a limit on the number of visas granted. The limit was 65,000 during these years, but the limit was only binding in 2004, 2005 and 2006.

For these years, I am using the ratio of the number of visas to be granted divided by the number of applications, adjusting for an estimate of the number of LCA applications for universities, since they are not subject to the quota. In 2003, the last year when the cap was not binding, the number of H1B visas allowed was 195000, and the number of LCA applications were 259623. I am thus using the number (259623-195,000) as the estimate for the number of visas granted to institutions that do not fall under this cap. Then for every year, the ratio of H1B visas to LCA certified applications is = 65,000 / {number of LCA certifications in that year * (259623-

195,000) }. This ratio estimates a lower bound for the number of H1b visas that are granted to a firm. In 2006, business week released a list of top 200 H1b visa employers, and looking at the firms that are ranked between 175 and 200, the median ratio of LCA applications to H1b visas granted is 0.88. So clearly, firms that hire more H1B workers are more likely to get their visa granted, perhaps by filling in forms correctly and using experienced lawyers etc. But at this point, I am using the most conservative adjustment factor.

Table 9d investigates the parameters if we restrict the sample to only high tech industries. In previous analysis we have seen that high skilled immigrant labor is much more likely to be hired by firms that fall in a high tech industry. We investigate this in two ways, first we restrict the sample to only high tech firms. In models 6-10, the assumption is that all LCA applications are H1B visas. In models 1-5, we use the conservative estimate of H1B visas using the adjustment factor. In either case, the conclusions do not change from the overall picture.

Table 9e investigates these parameters using interaction terms, as an alternative way to measure the different effect of the independent variables on output. The additional insight we get from this specification is that the Research and Development expenditure is relevant only for the high tech industries, and not for non-high tech industries. The coefficients of interest, shares of immigrant workers, both H1B and Permanent, still remain insignificant.

One last check is done in table 9f, where I restrict the model to only the years when the H1B cap was not binding. In my sample, these are years 2001 to 2003. The assumption here is that the number of certifications for both permanent resident applications and h1b applications is equal to the visas granted. Even in this specification, the shares of immigrants are not significant.

Discussion

Thus far, I cannot find evidence to support the hypothesis that high skilled immigrants are more productive than natives. I have made a few robustness checks and it seems that this conclusion is consistent. Looking at only the high-tech industries, which, as was revealed in the analysis, hires more H1b and Permanent Resident workers, results do not change either.

Further research needs to be done on whether the assumption of perfect substitutability is legitimate. The next step in this paper will be to relax this assumption and see if the results differ. Another extension which is part of my future work on this paper is to see whether measuring efficiency by the total factor productivity of the firm will reveal greater insights on the effect that high skilled immigrants have on firms in the US.

My findings at this point are more in line with Paserman's work than with Peri and Sparber's paper.

Table 7a – Dependent Variable is the number of LCA Applications by firms. Tobit regression model.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
employeecount	0.6973***	0.6659***	0.6213***	0.6931***					
	(0.0792)	(0.0778)	(0.0703)	(0.0781)					
employee_sq	-0.0006***	-0.0006***	-0.0006***	-0.0006***					
	(0.0001)	(0.0001)	(0.0001)	(0.0001)					
firm101to200					48.2727***	0.3110	47.0065***	45.0688***	42.3647***
					(7.7201)	(0.8609)	(17.5516)	(15.3603)	(12.8061)
firm201to1000					77.6194***	4.3148***	78.0900***	70.2758***	69.1620***
					(10.9230)	(0.7251)	(24.2923)	(25.5253)	(22.3940)
firm1001to2000					73.8915***	8.6845***	80.8747***	72.8140***	76.5149***
					(10.4063)	(1.3721)	(24.4094)	(26.7179)	(23.2758)
firmover2000					93.7651***	34.7393***	114.1793***	105.9914***	114.3960***
					(12.6057)	(7.4755)	(31.5822)	(36.9982)	(36.2128)
RnD					0.0435***	0.0716***	0.0549**	0.0582***	0.0551**
					(0.0084)	(0.0150)	(0.0249)	(0.0221)	(0.0247)
anyRD	28.7842***	28.9874***	30.6080***	8.2648***	23.4170***	5.7942*	32.0695***	54.3010***	51.3168***
	(4.0986)	(4.1150)	(4.3186)	(2.9589)	(4.8715)	(3.3003)	(8.6307)	(18.9228)	(15.7710)
K_L_ratio	-0.0088***	-0.0089***	-0.0088***	-0.0119***	-0.0042	-0.0006	-0.0032	-0.0013	-0.0001
	(0.0021)	(0.0021)	(0.0021)	(0.0027)	(0.0047)	(0.0014)	(0.0056)	(0.0029)	(0.0007)
outputshare_3			111.9917***	182.1150***	189.7297***	190.4671***	209.3252***	144.8294**	306.1502**
			(27.2463)	(33.2363)	(44.2192)	(68.3549)	(78.5804)	(72.0257)	(152.2888)
hightech				60.9903***	63.5864***	33.4437***	60.1798***		
				(7.1873)	(8.7066)	(4.5716)	(19.1875)		
outputshare_2		122.8039**							
		(55.9548)							
LCA_annualwage						-0.0001**			
						(0.0000)			
State FE							X	X	X
Industry 2 dg FE								X	

Industry 3 dg FE									X
Year FE							X	X	X
Observations	46,905	46,803	46,803	46,803	23,686	5,961	23,686	23,686	23,686
Pseudo R-squared	0.00414	0.00418	0.00444	0.0124	0.0210	0.0137	0.0515	0.0524	0.0584
Left Censored Obs	37916	37820	37820	37820	17725	0	17725	17725	17725
Uncensored Obs	8989	8983	8983	8983	5961	5961	5961	5961	5961
Clusters	.	.	.	.	.	.	52	23	85

Notes: tobit regression model with left censoring at zero. The errors were robust newey-west errors for models 1 -6, then clustered on state in model 7, clustered on 2 digit industry in model 8 and 3 digit industry in model 9.

Table 7b – Dependent Variable is the number of PERM Applications by firms. Tobit regression model.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
employeecount	0.2957***	0.3023***	0.2767***	0.3080***					
	(0.0372)	(0.0391)	(0.0344)	(0.0379)					
employee_sq	-0.0002***	-0.0002***	-0.0002***	-0.0002***					
	(0.0000)	(0.0000)	(0.0000)	(0.0000)					
firm101to200					23.1737***	-0.1871	19.7482***	18.8523***	17.5437***
					(3.5027)	(0.5133)	(4.2915)	(2.8862)	(3.1066)
firm201to1000					45.8391***	1.2489***	41.7259***	37.0789***	35.7223***
					(5.3775)	(0.4299)	(5.6876)	(7.5806)	(7.0133)
firm1001to2000					48.2955***	2.2429***	47.7350***	42.2382***	43.0184***
					(5.6509)	(0.6988)	(6.1826)	(9.8353)	(9.2004)
firmover2000					55.9222***	9.7636***	61.9966***	57.8198***	60.5104***
					(5.8159)	(2.7773)	(7.4732)	(10.6597)	(10.9809)
RnD					0.0209***	0.0335***	0.0264**	0.0280***	0.0267**
					(0.0040)	(0.0074)	(0.0108)	(0.0088)	(0.0121)
anyRD	14.7500***	14.7757***	15.2983***	2.6745	8.2497***	-3.2443	11.2500***	16.7346***	13.2874***
	(2.1919)	(2.1937)	(2.2718)	(1.6301)	(2.0913)	(2.2084)	(2.6891)	(4.2065)	(4.2514)
K_L_ratio	-0.0031	-0.0031	-0.0031	-0.0040	-0.0177	-0.0051	-0.0087	-0.0028	0.0003
	(0.0023)	(0.0023)	(0.0023)	(0.0028)	(0.0141)	(0.0052)	(0.0068)	(0.0051)	(0.0003)
outputshare_3			30.1708***	68.5163***	78.9392***	35.8226	86.9603***	57.2255	129.5299*
			(11.1157)	(13.5607)	(17.5105)	(28.4012)	(29.9654)	(39.3563)	(70.8917)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
hightech				32.9659***	35.7881***	14.5127***	31.6754***		
				(3.6900)	(4.1186)	(2.0387)	(5.8352)		
outputshare_2		-25.8717							
		(30.8864)							
PERM_annualwage						0.0000			
						(0.0000)			
State FE							X	X	X
Industry 2 dg FE								X	
Industry 3 dg FE									X
Year FE							X	X	X
Observations	46,974	46,872	46,872	46,872	23,733	3,656	23,733	23,733	23,733
Pseudo R-squared	0.00707	0.00708	0.00722	0.0229	0.0443	0.0246	0.0790	0.0798	0.0902
Left Censored Obs	41889	41793	41793	41793	20077	0	20077	20077	20077
Uncensored Obs	5085	5079	5079	5079	3656	3656	3656	3656	3656
Clusters	.	.	.	.	.	.	52	23	85

Notes: tobit regression model with left censoring at zero. The errors were robust newey-west errors for models 1 -6, then clustered on state in model 7, clustered on 2 digit industry in model 8 and 3 digit industry in model 9.

Table 8a – Baseline1

VARIABLES	(1) log_sales	(2) log_sales	(3) log_sales	(4) log_sales	(5) log_sales	(6) log_sales
log_RnD	-0.0194***	-0.0479***	-0.0603***	-0.0773***	-0.0518***	-0.0716***
	(0.0033)	(0.0042)	(0.0118)	(0.0138)	(0.0122)	(0.0142)
log_netcapital	0.0672***	0.0727***	0.0923***	0.1031***	0.0867***	0.0994***
	(0.0072)	(0.0071)	(0.0155)	(0.0125)	(0.0158)	(0.0117)
log_materials	0.5572***	0.5724***	0.5615***	0.5728***	0.5639***	0.5759***
	(0.0091)	(0.0091)	(0.0268)	(0.0228)	(0.0272)	(0.0232)
log_Lemployees	0.5036***	0.5140***	0.5167***	0.5131***	0.5105***	0.5078***
	(0.0105)	(0.0105)	(0.0431)	(0.0312)	(0.0482)	(0.0332)
hightech		0.2061***	0.2210***	0.1508***	0.2281***	0.1592***
		(0.0127)	(0.0098)	(0.0320)	(0.0101)	(0.0315)
State FE			X	X		

	(1)	(2)	(3)	(4)	(5)	(6)
Industry 2 dg FE			X		X	
Industry 3 dg FE				X		X
Firm FE						
Year FE			X	X	X	X
Observations	16,975	16,975	16,975	16,975	16,975	16,975
R-squared	0.9455	0.9464	0.9481	0.9492	0.9473	0.9484
Number of firms	3,954	3,954	3,954	3,954	3,954	3,954

Notes: Log of sales regressed on materials, capital, R&D, labor. Newey-West standard errors were used in models 1 and 2. Models 3, 4, 5 and 6 the errors were clustered on the 3 digit or 2 digit industry group, depending on which fixed effects were used.

Table 8b – Baseline2

VARIABLES	(1) log_sales	(2) log_sales	(3) log_sales	(4) log_sales	(5) log_sales	(6) log_sales
log_RnD	-0.0243***	-0.0526***	-0.0642***	-0.0798***	-0.0571***	-0.0749***
	(0.0036)	(0.0044)	(0.0131)	(0.0145)	(0.0133)	(0.0151)
log_capitalinvestment	0.0252***	0.0243***	0.0248***	0.0225***	0.0297***	0.0256***
	(0.0076)	(0.0076)	(0.0073)	(0.0063)	(0.0074)	(0.0065)
log_netcapital	0.0453***	0.0515***	0.0699***	0.0831***	0.0607***	0.0771***
	(0.0092)	(0.0091)	(0.0114)	(0.0113)	(0.0121)	(0.0109)
log_materials	0.5582***	0.5730***	0.5619***	0.5715***	0.5638***	0.5741***
	(0.0090)	(0.0090)	(0.0260)	(0.0223)	(0.0264)	(0.0226)
log_Lemployees	0.5011***	0.5119***	0.5142***	0.5108***	0.5086***	0.5061***
	(0.0104)	(0.0105)	(0.0445)	(0.0309)	(0.0495)	(0.0330)
hightech		0.2046***	0.2183***	0.1532***	0.2247***	0.1611***
		(0.0125)	(0.0090)	(0.0297)	(0.0091)	(0.0294)
State FE			X	X		
Industry 2 dg FE			X		X	
Industry 3 dg FE				X		X
Firm FE						
Year FE			X	X	X	X
Observations	16,704	16,704	16,704	16,704	16,704	16,704

R-squared	0.9458	0.9468	0.9484	0.9495	0.9476	0.9487
Number of firms	3,926	3,926	3,926	3,926	3,926	3,926

Notes: Log of sales regressed on materials, capital, R&D, labor. Newey-West standard errors were used in models 1 and 2. Models 3, 4, 5 and 6 the errors were clustered on the 3 digit or 2 digit industry group, depending on which fixed effects were used.

Table 9a – Measuring the effect of immigrants on firm productivity using the assumption that immigrants are completely substitutable but may have different marginal productivities compared to natives.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	D.log_sales	D.log_sales	D.log_sales	D.log_sales	D.log_sales	D.log_sales	D.log_sales
D.log_RnD	-0.0370***	-0.0370***	-0.0362	-0.0354*	-0.0352	-0.0347*	-0.0347***
	(0.0106)	(0.0106)	(0.0250)	(0.0197)	(0.0253)	(0.0196)	(0.0113)
D.log_netcapital	0.0360**	0.0358**	0.0402**	0.0398**	0.0404**	0.0399**	0.0399***
	(0.0148)	(0.0149)	(0.0187)	(0.0181)	(0.0183)	(0.0177)	(0.0148)
D.log_materials	0.4637***	0.4637***	0.4654***	0.4624***	0.4660***	0.4628***	0.4628***
	(0.0203)	(0.0203)	(0.0512)	(0.0395)	(0.0511)	(0.0396)	(0.0262)
D.log_Lemployees	0.4762***	0.4762***	0.4685***	0.4685***	0.4700***	0.4697***	0.4697***
	(0.0264)	(0.0264)	(0.0502)	(0.0372)	(0.0498)	(0.0374)	(0.0287)
sharePERMcertified	-0.5489	-0.5296	-0.5308	-0.3992	-0.4827	-0.3342	-0.3342
	(0.5252)	(0.5256)	(0.6973)	(0.5481)	(0.7507)	(0.5717)	(0.5863)
shareLCAcertified	-0.0085	-0.0063	-0.0368	-0.0290	-0.0329	-0.0239	-0.0239
	(0.1070)	(0.1069)	(0.0702)	(0.0531)	(0.0680)	(0.0551)	(0.1065)
hightech		-0.0052					
		(0.0058)					
State FE			X	X			
Industry 2 dg FE			X		X		
Industry 3 dg FE				X		X	X
Year FE			X	X	X	X	X
Observations	12,015	12,015	12,015	12,015	12,015	12,015	12,015
R-squared	0.4323	0.4323	0.4397	0.4465	0.4369	0.4443	0.4443
Number of firms	2,964	2,964	2,964	2,964	2,964	2,964	2,964

Notes: First difference of log of sales regressed on materials, capital, R&D, labor, and share of LCA and PERM applications. Newey-West standard errors were used in models 1 and 2. Models 3, 4, 5, 6 and 7 the errors were clustered on the 3 digit or 2 digit industry group, depending on which fixed effects were used.

Table 9b – Dependent variable is the first difference of the log of sales.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	D.log_sales	D.log_sales	D.log_sales	D.log_sales	D.log_sales	D.log_sales	D.log_sales
D.log_RnD	-0.0407***	-0.0407***	-0.0396	-0.0381*	-0.0387	-0.0374*	-0.0374***
	(0.0104)	(0.0104)	(0.0242)	(0.0190)	(0.0247)	(0.0190)	(0.0110)
D.log_capitalinvestment	0.0089	0.0089	0.0064	0.0063	0.0066	0.0063	0.0063
	(0.0062)	(0.0062)	(0.0046)	(0.0053)	(0.0045)	(0.0053)	(0.0065)
D.log_netcapital	0.0236	0.0234	0.0297*	0.0291	0.0298*	0.0292	0.0292*
	(0.0159)	(0.0159)	(0.0159)	(0.0200)	(0.0154)	(0.0196)	(0.0167)
D.log_materials	0.4610***	0.4610***	0.4639***	0.4611***	0.4644***	0.4615***	0.4615***
	(0.0209)	(0.0209)	(0.0507)	(0.0400)	(0.0506)	(0.0401)	(0.0271)
D.log_Lemployees	0.4945***	0.4945***	0.4877***	0.4878***	0.4892***	0.4888***	0.4888***
	(0.0266)	(0.0266)	(0.0399)	(0.0313)	(0.0393)	(0.0313)	(0.0289)
sharePERMcertified	-0.3398	-0.3170	-0.3356	-0.1931	-0.2691	-0.1107	-0.1107
	(0.5150)	(0.5153)	(0.7330)	(0.5833)	(0.7973)	(0.6188)	(0.5800)
shareLCAcertified	-0.0518	-0.0490	-0.0825	-0.0743	-0.0779	-0.0685	-0.0685
	(0.0935)	(0.0934)	(0.0759)	(0.0669)	(0.0746)	(0.0694)	(0.0958)
hightech		-0.0061					
		(0.0057)					
State FE			X	X			
Industry 2 dg FE			X		X		
Industry 3 dg FE				X		X	X
Firm FE							
Year FE			X	X	X	X	X
Observations	11,772	11,772	11,772	11,772	11,772	11,772	11,772
R-squared	0.4378	0.4378	0.4454	0.4523	0.4423	0.4497	0.4497
Number of firms	2,927	2,927	2,927	2,927	2,927	2,927	2,927

Notes: First difference of log of sales regressed on materials, capital, R&D, labor, and share of LCA and PERM applications. Newey-West standard errors were used in models 1 and 2. Models 3, 4, 5, 6 and 7 the errors were clustered on the 3 digit or 2 digit industry group, depending on which fixed effects were used.

Table 9 d – high-tech firms only

VARIABLES	(1) D.log_sales	(2) D.log_sales	(3) D.log_sales	(4) D.log_sales	(5) D.log_sales	(6) D.log_sales	(7) D.log_sales	(8) D.log_sales
D.log_RnD	-0.0568***	-0.0556**	-0.0546**	-0.0550**	-0.0567***	-0.0555**	-0.0545**	-0.0549**
	(0.0134)	(0.0219)	(0.0225)	(0.0225)	(0.0134)	(0.0219)	(0.0225)	(0.0225)
D.log_netcapital	0.0428**	0.0461**	0.0467**	0.0464**	0.0427**	0.0460**	0.0466**	0.0463**
	(0.0174)	(0.0210)	(0.0204)	(0.0211)	(0.0174)	(0.0209)	(0.0204)	(0.0211)
D.log_materials	0.4649***	0.4709***	0.4680***	0.4677***	0.4649***	0.4709***	0.4681***	0.4678***
	(0.0205)	(0.0431)	(0.0435)	(0.0435)	(0.0205)	(0.0431)	(0.0435)	(0.0435)
D.log_Lemployees	0.4879***	0.4804***	0.4815***	0.4802***	0.4877***	0.4802***	0.4813***	0.4801***
	(0.0306)	(0.0451)	(0.0447)	(0.0446)	(0.0305)	(0.0451)	(0.0446)	(0.0445)
sharePERMcertified	-0.8334	-0.5379	-0.5315	-0.6299	-0.7274	-0.4485	-0.4435	-0.5291
	(0.5602)	(0.6371)	(0.6470)	(0.6108)	(0.5718)	(0.6510)	(0.6601)	(0.6204)
shareLCAcertify_adjust	0.0304	0.0054	0.0112	0.0040				
	(0.1341)	(0.0577)	(0.0583)	(0.0548)				
shareLCAcertified					-0.0196	-0.0353	-0.0294	-0.0428
					(0.1342)	(0.0669)	(0.0648)	(0.0662)
Industry 3 dg FE			X	X			X	X
State FE				X				X
Firm FE								
Year FE		X	X	X		X	X	X
Observations	8,601	8,601	8,601	8,601	8,601	8,601	8,601	8,601
R-squared	0.4248	0.4292	0.4317	0.4345	0.4248	0.4292	0.4317	0.4345
Number of firms	2,119	2,119	2,119	2,119	2,119	2,119	2,119	2,119

Notes: Restricting the sample to only firms that are high tech, first difference of log of sales regressed on materials, capital, R&D, labor, and share of LCA and PERM applications. Newey-West standard errors were used in models 1 and 5. Models 2, 3, 4, 6, 7, and 8 the errors were clustered on the 3 digit or 2 digit industry group, depending on which fixed effects were used.

Table 9e – interaction terms with high tech

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	D.log_sales	D.log_sales	D.log_sales	D.log_sales	D.log_sales	D.log_sales	D.log_sales	D.log_sales
D.log_RnD	0.0060	0.0073	0.0098	0.0091	0.0060	0.0073	0.0098	0.0091
	(0.0166)	(0.0166)	(0.0235)	(0.0234)	(0.0166)	(0.0166)	(0.0235)	(0.0234)
D.log_netcapital	0.0106	0.0122	0.0177	0.0173	0.0106	0.0122	0.0177	0.0173
	(0.0258)	(0.0258)	(0.0316)	(0.0312)	(0.0258)	(0.0258)	(0.0316)	(0.0312)
D.log_materials	0.4651***	0.4662***	0.4544***	0.4538***	0.4651***	0.4662***	0.4544***	0.4538***
	(0.0544)	(0.0549)	(0.0953)	(0.0953)	(0.0544)	(0.0549)	(0.0953)	(0.0953)
D.log_Lemployees	0.4472***	0.4433***	0.4328***	0.4306***	0.4472***	0.4433***	0.4328***	0.4306***
	(0.0529)	(0.0532)	(0.0476)	(0.0472)	(0.0529)	(0.0532)	(0.0476)	(0.0472)
hightech	-0.0027	-0.0029	-0.0011	-0.0049	-0.0026	-0.0027	-0.0010	-0.0048
	(0.0075)	(0.0075)	(0.0188)	(0.0186)	(0.0075)	(0.0075)	(0.0188)	(0.0186)
D.RnDhightech	-0.0628***	-0.0633***	-0.0645**	-0.0644**	-0.0628***	-0.0633***	-0.0644**	-0.0643**
	(0.0213)	(0.0213)	(0.0315)	(0.0312)	(0.0213)	(0.0213)	(0.0315)	(0.0312)
D.netcapitalhightech	0.0323	0.0331	0.0285	0.0288	0.0321	0.0330	0.0283	0.0286
	(0.0311)	(0.0311)	(0.0367)	(0.0361)	(0.0311)	(0.0311)	(0.0367)	(0.0360)
D.materialshightech	-0.0002	0.0034	0.0126	0.0129	-0.0002	0.0034	0.0126	0.0129
	(0.0581)	(0.0584)	(0.1039)	(0.1040)	(0.0581)	(0.0584)	(0.1039)	(0.1040)
D.Lemployeeshightech	0.0407	0.0385	0.0501	0.0514	0.0405	0.0383	0.0499	0.0512
	(0.0611)	(0.0613)	(0.0635)	(0.0626)	(0.0610)	(0.0613)	(0.0635)	(0.0626)
sharePERMcertified	0.9190	1.0066	0.8041	0.8225	0.9687	1.0377	0.7885	0.8125
	(1.5044)	(1.5175)	(1.4116)	(1.4084)	(1.4932)	(1.5080)	(1.4000)	(1.3900)
sharePERMhightech	-1.7524	-1.6183	-1.3916	-1.4931	-1.6961	-1.5503	-1.2815	-1.3782
	(1.6054)	(1.6203)	(1.5436)	(1.5074)	(1.5990)	(1.6154)	(1.5684)	(1.5229)
shareLCAcertify_adjust	-0.0118	-0.0141	-0.0561	-0.0510				
	(0.1168)	(0.1183)	(0.1409)	(0.1377)				

shareLCAhightechadjust	0.0422	0.0272	0.0729	0.0637				
	(0.1778)	(0.1802)	(0.1559)	(0.1508)				
shareLCAcertified					-0.0232	-0.0211	-0.0524	-0.0487
					(0.1167)	(0.1178)	(0.1362)	(0.1332)
shareLCAhightech					0.0035	-0.0113	0.0252	0.0122
					(0.1779)	(0.1797)	(0.1564)	(0.1514)
Industry 3 dg FE			X	X			X	X
State FE				X				X
Year FE		X	X	X		X	X	X
Observations	12,015	12,015	12,015	12,015	12,015	12,015	12,015	12,015
R-squared	0.4336	0.4367	0.4456	0.4479	0.4336	0.4367	0.4456	0.4479

Notes: Each of the independent variables are now interacted with a high tech dummy. First difference of log of sales regressed on materials, capital, R&D, labor, and share of LCA and PERM applications. Newey-West standard errors were used in models 1, 2, 5 and 6. Models 3, 4, 7, 8 9 the errors were clustered on the 3 digit industry group.

Table 9f – Only for years 2001-2003, when the H1B cap was not binding.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	D.log_sales	D.log_sales	D.log_sales	D.log_sales	D.log_sales	D.log_sales	D.log_sales
D.log_RnD	-0.0434***	-0.0434***	-0.0425	-0.0415*	-0.0414	-0.0407*	-0.0407**
	(0.0153)	(0.0153)	(0.0255)	(0.0230)	(0.0253)	(0.0227)	(0.0162)
D.log_netcapital	0.0129	0.0129	0.0222	0.0216	0.0224	0.0217	0.0217
	(0.0212)	(0.0213)	(0.0192)	(0.0198)	(0.0191)	(0.0193)	(0.0222)
D.log_materials	0.4778***	0.4778***	0.4721***	0.4663***	0.4725***	0.4661***	0.4661***
	(0.0245)	(0.0245)	(0.0603)	(0.0455)	(0.0607)	(0.0456)	(0.0269)
D.log_Lemployees	0.5117***	0.5117***	0.5025***	0.5009***	0.5043***	0.5018***	0.5018***
	(0.0393)	(0.0393)	(0.0707)	(0.0496)	(0.0714)	(0.0500)	(0.0416)
sharePERMcertified	-0.6030	-0.5995	-0.7071	-0.5169	-0.7121	-0.5041	-0.5041
	(0.6413)	(0.6419)	(0.5135)	(0.4495)	(0.6359)	(0.4932)	(0.6974)
shareLCAcertified	0.0513	0.0513	0.0400	0.0282	0.0448	0.0320	0.0320

	(0.1171)	(0.1171)	(0.0627)	(0.0666)	(0.0632)	(0.0644)	(0.1155)
hightech		-0.0009					
		(0.0086)					
State FE			X	X			
Industry 2 dg FE			X		X		
Industry 3 dg FE						X	X
Year FE			X	X	X	X	X
Observations	6,353	6,353	6,353	6,353	6,353	6,353	6,353
R-squared	0.4128	0.4128	0.4230	0.4349	0.4178	0.4312	0.4312
Number of Firms	2528.	2528	2528	2528	2528	2528	2528

Notes: First difference of log of sales regressed on materials, capital, R&D, labor, and share of LCA and PERM applications. Newey-West standard errors were used in models 1, and 2. Models 3 to 7 the errors were clustered on the 3 digit or 2 digit industry group as appropriate.