ESSAYS ON GLOBALIZATION AND FIRM PERFORMANCE

by

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to my parents
for all of their sacrifices, love, and support

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CHAPTER I

Introduction

This dissertation consists of three essays broadly relating to globalization and firm performance. In the first essay, we address a relatively open question in the area of immigration: how do large inflows of highly skilled immigrants affect the rate of domestic innovation? We study this question in the context of the H-1B visa program, which is the primary temporary visa for work in the US. Immigrants constitute a large share of US inventors; foreign born workers account for 24 percent of scientists and engineers with bachelor's degrees and 47 percent of those with doctoral degrees. We find that larger inflows of highly skilled immigrants are associated with higher rates of innovation. This relationship is primarily driven by the contributions of the immigrants themselves. We find some tentative evidence for the crowding in of inventors who are US citizens and can reject the hypothesis that they are crowded out. These results suggest that there may be complementarities between foreign and domestic inventors.

The second essay explores the rise of worldwide trade since 1987. In particular, we look at the growth in the number of varieties traded internationally from the perspective of the experience of the United States. Using data from the US Census, we find that the percentage of plants with 20 or more employees rose from 21 percent in 1987 to 39 percent in 2006. This mirrors the tripling of the number of varieties of goods imported into the US over 1971 to 2001 documented by Broda and Weinstein (2004). In discussing the causes of similar trends in other countries, prior authors have suggested the natural explanation that the large scale foreign market entry that we see in the data may be driven by declines in the up-front costs of entering foreign markets. We look at this idea empirically for the first time and find little evidence that these trends have been driven by substantial declines in these costs. In doing so, we consider a number of descriptive statistics as well as reduced form and structural estimations. We instead make the case that these trends were caused by changes in other factors that determine export market status, such as economic growth in foreign countries.

In the final chapter, we explore firms' efforts to influence public policies as a means of increasing their profits. Specifically, we look at whether there exist up-front costs to engaging in lobbying the federal government and whether these barriers affect firm behavior. Lobbying is the primary avenue through which firms attempt to affect policy outcomes, with firm lobbying expenditures outnumbering campaign contributions by a factor of nine. Ours is the first to look at the determinants of lobbying behavior over time. The idea that these up-front costs exist has a long history in the political science literature and ours is the first work to evaluate it empirically. We develop and estimate an empirical model, finding strong support for the existence of these costs. We argue that these barriers to entry help explain three facts about lobbying (i) few firms lobby, (ii) lobbying status is strongly associated with firm size, and (iii) lobbying status is highly persistent over time. We then look at this question from the perspective of a particular policy change: the dramatic decline in the number of H-1B visas that could be allotted that occurred in 2004. We find significant adjustments into lobbying for immigration by firms already lobbying for other issues but little change by firms that were not previously lobbying. We argue that these results also suggest the existence of barriers to entry in the lobbying process.

CHAPTER II

The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention

2.1 Introduction

The H-1B visa program governs most admissions of temporary immigrants into the US for employment in science and engineering (SE). This program has become a point of significant controversy in the public debate over immigration, with proponents and detractors at odds over how important H-1B admission levels are for US technology advancement and whether native US workers are being displaced by immigrants. This chapter quantifies the impact of changes in H-1B admission levels on the pace and character of US invention over the 1995-2008 period. We hope that this assessment aids policy makers in their current decisions about appropriate admission rates in the future.

The link between immigration policy and innovation may appear tenuous at first, but immigrant scientists and engineers are central to US technology formation and commercialization. Immigrants represented 24% and 47% of the US SE workforce with bachelor's and doctorate educations in the 2000 Census, respectively. This contribution was significantly higher than the 12% share of immigrants in the US working population. The growth of this importance in recent years is even more striking. From the Current Population Survey (CPS), we estimate that immigrant scientists and engineers accounted for more than half of the net increase in the US SE labor force since 1995.

Greater inflows and employment shares of educated immigrants do not necessarily increase the pace of US innovation, however. Aggregate innovation could be unaffected, for example, if immigrants displace natives. To disentangle these issues, it is possible to exploit variation across dimensions like geography and industry. Establishing this variation is quite challenging with standard data sources, however, and partial correlations may not identify causal relationships in this context due to the endogeneity of immigrant location decisions.

To bring identification to this question, we exploit large changes in the H-1B worker population over the 1995-2008 period. The national cap on new H-1B admissions fluctuated substantially over these years, ranging from a low of 65,000 new workers a year to a high of 195,000. SE and computer-related occupations account for approximately 60% of H-1B admissions, and changes in the H-1B population account for a significant share of the growth in US immigrant SE employment. In a reduced-form framework closely related to Card (2001), our empirical approach considers differences across US firms, cities, and states due to fluctuations in the H-1B population.

We first analyze CPS employment records for 1995-2008 using state-level variation. Growth in the H-1B program was associated with increased employment growth for immigrant scientists and engineers, especially among non-citizen immigrants. A 10% growth in the national H-1B population corresponded with a 2%-4% higher growth in immigrant SE employment for each standard deviation increase in state dependency. We do not find any substantive effect on native scientists and engineers across a range of labor market outcomes like employment levels, mean wages, and unemployment rates. We are able to rule out crowding-out effects, and our results suggest potentially small crowding-in effects. The total SE workforce in the state increased mainly through the direct contributions of immigrants. A 10% growth in the national H-1B population corresponded with about a 0.5% higher growth in total SE employment for each standard deviation increase in state dependency.

While the CPS data afford direct observation of employment, wages, and immigration status, the data also have substantive limitations. To make additional progress and to more closely study the link between the H-1B program and US innovation, we devote the rest of the chapter to characterizing differences in patenting behavior across cities and firms. We assemble micro-data on all US patent grants and applications through May of 2009. These base patent records offer complete patenting histories annually for cities and firms. Moreover, while immigration status is not directly observed, we can identify the probable ethnicities of inventors through their names. For example, inventors with the last names Gupta or Desai are more likely to be Indian than they are to be Anglo-Saxon or Vietnamese. This micro-level detail also allows us to analyze situations where no other data exist (e.g., how the H-1B program impacts the annual patenting contributions of Indian ethnicity inventors within Intel versus Proctor & Gamble).

We find that increases in H-1B admissions substantially increased rates of Indian and Chinese invention in dependent cities relative to their peers. A 10% growth in the H-1B population corresponded with a 1%-4% higher growth in Indian and Chinese invention for each standard deviation increase in city dependency. We again find very little impact for native inventors as proxied by inventors with Anglo-Saxon names (who account for approximately 70% of all domestic patents). The evidence does not support crowding-out theories, and there is suggestive support for small crowding-in effects. Overall, a 10% growth in the H-1B population corresponded with a 0.3%-0.7% increase in total invention for each standard deviation growth in city dependency.

These city-level findings are robust to including a variety of regression controls like expected technology trends, labor market conditions, and region-year fixed effects. We also examine effects throughout the city dependency distribution and drop very dependent cities, firms, and sectors (e.g., computer-related patents). These tests help to confirm that our results are not due to endogenous changes in national H-1B admissions following lobbying from very dependent groups. Finally, we show that our results for US cities are not reflected in a placebo experiment involving shifts in ethnic invention among Canadian cities. Section 2.4 also discusses some limitations of our analysis, especially around the lag structure of treatment effects.

Our firm-level analysis creates a panel of 77 publicly listed firms that account for about a quarter of US patents. Within this group, we again find that invention rates of more H-1B dependent firms are particularly sensitive to the size of the program. A 10% growth in the H-1B population corresponded with a 4%-5% higher growth in Indian and Chinese invention for each standard deviation increase in firm dependency. These elasticities are particularly strong for computer-oriented firms (e.g., Microsoft, Oracle) relative to firms in other sectors.

Our research most directly relates to recent empirical studies on the relationship between immigration and US innovation. Peri (2007) and Hunt and Gauthier-Loiselle (2008) explore long-run relationships between immigration and patenting rates using state-decade variation. The latter study in particular finds substantial crowding-in effects for native scientists and engineers. Chellaraj et al. (2008) also find strong crowding-in effects when using time-series variation. In contrast, Borjas (2005, 2006) finds that natives are crowded-out from graduate school enrollments by foreign students, especially in the most elite institutions, and suffer lower wages after graduation due to increased labor supply. This disagreement in the academic literature is reflected in the public debate over high-skilled immigration and the H-1B visa in particular.

Our work contributes to this research through its measurement of ethnic patenting and the use of H-1B policy changes for the identification of immigrant SE inflows. Our limited effects for natives fall in between the results of prior academic work and the effects suggested in the public debate. This may reflect the high-frequency variation that we exploit and institutional features of the H-1B program that we discuss below. We also contribute to the literature through the first description of ethnic invention within firms and the first characterization of the firm-level link between immigration and innovation. Understanding these mechanisms is important as immigration policies influence firms, universities, and other institutions differently.[1]

In a broader context, we view our research as a building block for describing the supply side of innovation. The demand side of the economy governs the pace of innovation in most models of endogenous growth; larger markets encourage greater entrepreneurial innovation due to profit incentives. In these basic frameworks, labor adjusts freely across research and production sectors, and high-skilled labor inflows do not increase innovation except trivially through larger economy size. There are, however, at least two deeper channels through which immigration can influence in-

[1]Note that the original version of this chapter appeared in the Journal of Labor Economics vol. 28(3), ©2010 by The University of Chicago. Related papers describing the contributions of immigrants to US science and engineering include Stephan and Levin (2001), Saxenian (2002), Matloff (2003, 2004), Miano (2005, 2008), NFAP (2008), Lowell and Christian (2000), Wadhwa et al. (2007), Kerr (2008), and Hunt (2009). Freeman (2006) surveys global labor flows and discusses their deep scientific impacts. General surveys of immigration include Borjas (1994), Friedberg and Hunt (1995), and Kerr and Kerr (2008). Foley and Kerr (2008) examine the firm-level link between immigration and FDI.

novation. First, there are often significant adjustment costs when workers move across occupations and sectors, particularly when moving into research-oriented occupations. These slower adjustments open up the possibility for supply shocks to US innovation through shifts in immigration policy. Second, the sharing of ideas across countries can lead directly to higher levels of innovation. We believe that these effects can be large with high-skilled immigration, especially when the knowledge needed to create new ideas is tacit. We hope that future research studies these mechanisms in greater detail.[2]

2.2 US Ethnic Invention

We quantify ethnic technology development in the US through the individual records of all patents granted by the United States Patent and Trademark Office (USPTO) from January 1975 to May 2009. Each patent record provides information about the invention (e.g., technology classification, firm or institution) and the inventors submitting the application (e.g., name, city). Hall et al. (2001) provide extensive details about these data, and Griliches (1990) surveys the use of patents as economic indicators of technology advancement. The data are extensive, with over eight million inventors and four million granted patents during this period.

While immigration status is not collected, one can determine the probable ethnicities of inventors through their names. USPTO patents must list at least one inventor, and multiple inventors are often listed. Our approach exploits the idea that inventors with the surnames Chang or Wang are likely of Chinese ethnicity, those with surnames Rodriguez or Martinez of Hispanic ethnicity, etc. Two com-

[2]For related research on these issues, see Acemoglu and Linn (2004), Barro and Sala-i-Martin (1995), Freeman (1971), Siow (1984), Rivera-Batiz and Romer (1991), Ryoo and Rosen (2004), and Furman et al. (2002).

mercial ethnic name databases originally used for marketing purposes are utilized, and the name-matching algorithms have been extensively customized for the USPTO data. The match rate is 99%. Kerr (2007) provides further details on the matching process, lists frequent ethnic names, and provides multiple descriptive statistics and quality assurance exercises. As our regressions employ ethnic patenting for dependent variables, remaining measurement error in inventor ethnicities will not substantively influence the consistency of our estimates.[3]

Figure 2.1 illustrates the evolving ethnic contribution to US technology development as a percentage of patents granted by the USPTO. These descriptive statistics and the regression analyses below only use patents filed by inventors residing in the US (with the exception of the Canadian regressions). When multiple inventors exist on a patent, we make individual ethnicity assignments for each inventor and then discount multiple inventors such that each patent receives the same weight. We group patents by the years in which they applied to the USPTO. For presentation purposes, Figure 2.1 does not include the Anglo-Saxon and European ethnic shares. They jointly decline from 90% of total US domestic patents in 1975 to 76% in 2004. This declining share is primarily due to the exceptional growth over the 30 years of the Chinese and Indian ethnicities, which increase from under 2% to 9% and 6%, respectively.

We define cities through 281 Metropolitan Statistical Areas. In descriptive analyses, we find that ethnic inventors are generally concentrated in gateway cities closer to their home countries (e.g., Chinese in San Francisco, Hispanics in Miami). Not surprisingly, total patenting shares are highly correlated with city size, and the three

[3] One of our quality assurance exercises regards the estimated ethnic composition of foreign patents registered with the USPTO. The resulting compositions are quite reasonable. About 90% of inventors filing from India and China are classified as ethnically Indian and Chinese, respectively. This is in line with what we would expect, as native shares should be less than 100% due to the role that foreign inventors play in these countries.

largest shares of US domestic patenting for 1995-2004 are San Francisco (12%), New York City (7%), and Los Angeles (6%). Ethnic patenting is generally more concentrated, with shares for San Francisco, New York City, and Los Angeles being 22%, 10%, and 9%, respectively. Indian and Chinese invention are even further agglomerated. San Francisco shows exceptional growth from an 8% share of total US Indian and Chinese patenting in 1975-1984 to 26% in 1995-2004, while New York City's share declines from 17% to 10%.[4]

Figures 2.2 and 2.3 provide a more detailed view of Indian and Chinese contributions for different technology sectors. These two ethnicities are more concentrated in high-tech sectors than in traditional fields, and their growth as a share of US innovation in the 1990s is remarkable. A large portion of this growth is due to the rapid economic development of these countries and their greater SE integration with the US. Similarly, sustained US economic growth made America attractive as a host country. The US Immigration Act of 1990 also facilitated greater permanent immigration of SE workers from large countries like India and China (e.g., Kerr 2008).

Figure 2.2 exhibits an interesting downturn in the Indian share of computer-related invention after 2000, which includes software patents. This shift from strong growth in the 1990s is striking and may reflect more restrictive US immigration policies. Many factors likely contributed to this shift, however, such as the high-tech recession and the increasing attractiveness of foreign opportunities like Bangalore. Accordingly, our estimations control for these aggregate trends.

As a final descriptive feature, it is important to assess whether major differences

[4] Agrawal et al. (2008) and Kerr (2009) further describe ethnic inventor agglomeration.

exist across ethnicities in the quality of innovations. The most tractable approach for our sample is to examine the number of claims made by patents filed by different ethnicities. Each patent includes a series of claims that delineate the property rights of the technology. These claims define the novel features of each invention from prior inventions and become a crucial factor in future patent infringement litigations. USPTO examiners review and modify the claims argued for by inventors in their applications, and several studies link the granted number of claims on a patent with its economic value. The average claims on Indian (19.7) and Chinese (18.9) patents are slightly above the sample average of 18.8. This comparability holds in simple regressions that control for technology category by year fixed effects.[5]

While the ethnic patenting data provide a tractable platform for examining immigration and innovation, several limitations exist. First, our approach does not distinguish between foreign-born inventors working in the US and later generations. Our panel econometrics, however, identify off of relative changes in ethnic inventor populations. For Indian and Chinese inventors, these changes are mainly due to new immigration or school-to-work transitions that require a visa, weakening this overall concern. Similarly, we study native outcomes through inventors with Anglo-Saxon names. In addition to capturing effects on US natives, inventors with Anglo-Saxon names also reflect some immigration from the UK, Canada, etc. Relative magnitudes suggest that this second factor is very small, however. Canada and the UK account for about 10,000 new H-1B workers annually over the 2000-2005 period, a small number compared to a native SE workforce of more than 2.5 million. Our CPS analysis further addresses these concerns.[6]

[5] Hunt (2009) finds that immigrants entering on temporary work visas or student/trainee visas typically outperform natives in patenting and related activities. This greater performance is mostly explained by immigrants' higher education and selected fields of study. Thus, the disproportionate contributions of immigrant scientists and engineers come primarily through greater involvement and training for SE fields.

[6] The base data contain information on all patents granted from January 1975 to May 2009. Application years

2.3 H-1B Visa Program

The H-1B visa is a temporary immigration category that allows US employers to seek short-term help from skilled foreigners in "specialty occupations." These occupations are defined as those requiring theoretical and practical application of specialized knowledge like engineering or accounting; virtually all successful H-1B applicants have a bachelor's education or higher. The visa is used especially for SE and computer-related occupations, which account for roughly 60% of successful applications. Approximately 40% and 10% of H-1B recipients over 2000-2005 came from India and China, respectively. Shares for other countries are less than 5%.[7]

The sponsoring firm files the H-1B application and must specify an individual candidate. The employer-employee match must therefore be made in advance.[8] Workers are tied to their sponsoring firm, although some recent changes have increased visa portability. Firms can petition for permanent residency (i.e., a green card) on behalf of the worker. If permanent residency is not obtained, the H-1B worker must leave the US at the end of the visa period for one year before applying again. Firms are also required to pay the visa holder the higher of (1) the prevailing wage in the firm for the position or (2) the prevailing wage for the occupation in the area of employment. These restrictions were designed to prevent H-1B employ-

of patents, however, provide the best description of when innovative research is being undertaken due to substantial and uneven lags in USPTO reviews. Inventors also have strong incentives to file for patent protection as soon as their research project is sufficiently advanced. Accordingly, our annual descriptions are measured through patent application years. This standard approach leads to sample attrition after 2004 as many applications have not yet been processed for approval when our data were collected. To compensate for this, we also employ a data set of over one million published patent applications, which the USPTO began releasing in 2000. Our preferred data set combines the patent grants and applications data, removing applications that have been granted. This union yields more consistent sample sizes in later years. We also consider estimations that only use grants data in robustness checks and come to similar conclusions.

[7]Broad statistics on the H-1B program are taken from reports submitted annually to Congress: "Characteristics of Specialty Occupation Workers (H-1B)." Data on source countries compositions are only publicly available for the period 2000-2005. Lowell and Christian (2000), Lowell (2000), Matloff (2003), and Kirkegaard (2005) provide additional details on the H-1B program. Facchini et al. (2008) and Hunt (2009) overview other temporary immigration categories.

[8]Different employers can simultaneously seek visas for the same prospective employee, although firms generally make applications only on behalf of committed workers due to the time and legal fees involved. The application fee for a firm with 26 or more full-time employees was $2,320 in 2008.

ers from abusing their relationships with foreign workers and to protect domestic workers.[9]

Since the Immigration Act of 1990, there has been an annual cap on the number of H-1B visas that can be issued. The cap governs new H-1B visa issuances only; renewals for the second three-year term are exempt, and the maximum length of stay on an H-1B visa is thus six years. While most aspects of the H-1B program have remained constant since its inception, the cap has fluctuated significantly. The largest amount of controversy about the H-1B program focuses on this cap. Indeed, a search of Lexis-Nexis finds more than three thousand news articles about the visa from 1995-2006. Executives of high-tech firms often argue that higher H-1B admissions are necessary to keep US businesses competitive, to spur innovation and growth, and to keep firms from shifting their operations abroad. Detractors, on the other hand, argue that the program displaces American workers, lowers wages, and discourages on-the-job training.

Figure 2.4 uses fiscal year data from the United States Citizenship and Immigration Services (USCIS) to plot the evolution of the numerical cap.[10] The 65,000 cap was not binding in the early 1990s but became so by the middle of the decade. Legislation in 1998 and 2000 sharply increased the cap over the next five years to 195,000 visas. The language contained in the 1998 legislation argued that "American companies today are engaged in fierce competition in global markets" and "are faced with severe high-skill labor shortages that threaten their competitiveness." These short-term increases were allowed to expire during the US' high-tech downturn, when visa demand fell short of the cap. The cap returned to the 65,000 level in 2004 and became binding again, despite being subsequently raised by 20,000 through

[9] Studies of the impact of H-1Bs on wages are mixed and include Lowell (2001), Zavodny (2003), Matloff (2003, 2004), Kirkegaard (2005), Miano (2005), Tambe and Hitt (2009), Mithas and Lucas (2009), and Hunt (2009).

[10] The USCIS is the successor to the Immigration and Naturalization Service (INS).

an "advanced degree" exemption.[11]

These adjustments to the H-1B cap are large enough to be economically important. Back-of-the-envelope calculations using the CPS suggest that raising the H-1B cap by 65,000 visas would increase the US SE labor force by about 1.2%, holding everything else constant. This increase would be about half of the median annual growth rate of SE workers, calculated at 2.7% during the period. Thus, while the H-1B program does not have the size to dramatically alter aggregate levels of US invention in the short run, it does have the size to substantially influence the growth rate of US innovation, which is what our empirical specifications test. These effects on the growth of innovation can have very significant impacts on economic growth and aggregate welfare when compounded over time.

The two closest temporary worker visas to the H-1B are the L-1 and TN visas. Neither of these visa categories is a particularly good substitute for the H-1B. The L-1 is issued to multinationals in order to bring in managers or employees with "specialized knowledge" that have worked for the firm abroad for at least one year. The TN visa was established under NAFTA and allows citizens from Mexico and Canada to work in the US in certain high-skilled occupations. Both of these programs are less than 10% of the size of the H-1B program for high-tech workers during the 1995-2006 period and contain institutional features that limit firms' ability to use them to circumvent the H-1B quota. Neither visa category shows substantial increases after the H-1B cap was dramatically reduced in 2004, and the Department of Homeland

[11] The two legislations are the American Competitiveness and Workforce Improvement Act of 1998 and the American Competitiveness in the Twenty-First Century Act of 2000. See Reksulak et al. (2006) and Public Law 105-777, Division C, American Competitiveness and Workforce Improvement Law, Section 416(c)(2).

Unlike permanent immigration, immediate family members of the H-1B worker do not count towards the visa cap. These family members are, however, restricted from working unless they otherwise obtain an appropriate work visa. Free trade agreements require that 1,400 and 5,400 of the visas be reserved for citizens of Chile and Singapore, respectively. These special allotments are often under-utilized, however, and excess visas are returned to the general pool. In recent years, additional extensions have been granted for H-1B holders who are still waiting for permanent residency approval when their initial six years have expired.

Security has argued that limited substitution exists across the H-1B and L-1 visas.[12]

Prior research on the H-1B program is mostly descriptive due to data limitations. Indeed, data constraints significantly shape our empirical approach discussed below. The most important work for our purposes are estimates of the H-1B entry rates and population stocks, neither of which is definitively known. Lowell (2000) builds a demographic model for this purpose that factors in new admissions and depletions of the existing H-1B pool by transitions to permanent residency, emigration, or death. While H-1B inflows are reasonably well measured, the latter outflows require combining available statistics with modelling assumptions. In Lowell's model, emigration and adjustment to permanent residency are roughly comparable in magnitude, with the time spent from entry to either event being estimated through typical H-1B experiences.

Figure 2.4 shows Lowell's updated estimates. The H-1B population grew rapidly in the late 1990s before leveling off after 2000. The lack of growth immediately after 2000 can be traced to weak US employment opportunities for scientists and engineers during the high-tech recession. When demand returned, however, the reduced supply of H-1B visas restricted further growth. This constraint is obscured in Figure 2.4, where entry rates exceed the cap. This decoupling of the numerical cap and H-1B entry rates is due to the American Competitiveness in the Twenty-First Century Act of 2000. This legislation made universities, government research labs, and certain nonprofits exempt from the cap and took effect in fiscal year 2001. We consequently focus on patents from the private sector that remain subject to the cap and that constitute the vast majority of patents. We also test whether using Lowell's population estimates or a measure based solely on the cap influences our

[12]Our earlier working paper further discusses the L-1 and TN visas.

results.

Firms in particular remain subject to the cap, and their growth in H-1B usage has been constrained by recent lower admissions levels. USCIS begins accepting applications on April 1st for the following fiscal year and announces when the cap is reached. It has been reached in every fiscal year since the cap was lowered in 2004, often on the first day of accepting applications. A lottery has been used since 2006 among firms that applied close to the cut-off date. Whether or not a shortage of SE workers exists is strongly debated (e.g., Lowell and Salzman 2007). Unemployment rates for SE workers are typically quite low (e.g., Kannankutty 2008), but a number of studies document stagnating SE wages compared to similarly skilled occupations (e.g., Lemieux 2007).

Beyond these broad statistics, data regarding the H-1B program are very limited. Our primary data source in this regard is the published micro-records on Labor Condition Applications (LCAs). To obtain an H-1B visa, an employer must first file an LCA with the US Department of Labor (DOL). The primary purpose of the LCA is to demonstrate that the worker in question will be employed in accordance with US law. The second step in the application process after the LCA is approved is to file a petition with the USCIS, which makes the ultimate determination about the visa application. The DOL releases micro-records on all applications it receives, numbering 1.8 million for 2001-2006. These records include firm names and proposed work locations.[13] We use these data to describe both city and firm dependencies, although it should be noted that LCA approvals do not translate one-for-one into H-1B grants.

[13]Our earlier working paper describes in greater detail the preparation of our data.

2.4 Spatial Analyses of the H-1B Program

2.4.1 Empirical Framework

We seek to quantify the impact of changing H-1B admission levels on SE employment and innovation. We are unlikely to successfully capture this relationship using aggregate trends given the many contemporaneous changes to the US economy over the past two decades. We thus need to exploit variation across more narrowly defined labor markets within the US. Such variation allows us to control for national changes and thereby use relative differences in localized expansions or contractions to measure the H-1B program's effects.

We take cities to be the primary labor market for this analysis, a decision further discussed below. Defining H-1B$_{c,t}$ as the stock of H-1B immigrants in city c in year t, the impact of the H-1B program could in principle be estimated with a panel specification of the form

$$SE_{c,t} = \phi_c + \eta_t + \tilde{\beta} \cdot \ln(\text{H-1B}_{c,t}) + \tilde{\epsilon}_{c,t}. \tag{2.1}$$

where ϕ_c and η_t are city and year fixed effects. Year effects would control for aggregate time trends, and city effects would account for permanent differences across cities. The dependent variables of interest would include log employment of different types of SE workers, log SE wages, and log patents. The $\tilde{\beta}$ coefficient would measure how much growth in the local H-1B population impacted the corresponding outcome variable of interest.

There are several challenges, however, to specification (2.1). Most immediately, population estimates of H-1B$_{c,t}$ do not exist due to data constraints. Second, even if these data existed, the resulting model would likely return a biased estimate of the true $\tilde{\beta}$ parameter. Local H-1B populations are not randomly assigned, and their growth may be correlated with the error term $\tilde{\epsilon}_{c,t}$. The firm-sponsored nature of the visa and its intended use for labor scarcity, moreover, would make the direction of this endogeneity and resulting bias ambiguous.[14]

Due to these issues, we implement a variant of the supply-push immigration framework of Card (2001). We test whether shifts in national H-1B admissions are associated with stronger or weaker SE employment and innovation in cities that are very dependent upon the program relative to less dependent peers. Defining H-1B$_c$ as city c's fixed dependency on the program and H-1B$_t$ as the national H-1B population, the modified estimating framework is

$$SE_{c,t} = \phi_c + \eta_t + \beta \cdot [\text{H-1B}_c \cdot \ln(\text{H-1B}_t)] + \epsilon_{c,t}, \tag{2.2}$$

where main effects for H-1B$_c$ and ln(H-1B$_t$) are absorbed into the panel fixed effects. Thus, framework (2.2) only exploits the residual variation in the interaction for identification.

This equation is a reduced-form estimate of the true relationship (2.1). The β coefficient measures the impact of national H-1B population growth on outcomes of interest in more dependent versus less dependent cities. This approach properly identifies treatment effects if (1) national H-1B admission decisions are made exogenously by the federal government, (2) the national changes have heterogeneous impacts across cities due to differences in fixed dependencies, and (3) neither of the terms are correlated with omitted factors that also shape SE employment and

[14]For example, an upward bias for native employment outcomes may result from localized productivity or technology shocks simultaneously increasing H-1B and native SE labor demand. On the other hand, a downward bias may result from situations where firms employ H-1B workers to overcome a declining ability to attract native SE workers to the city (e.g., due to weakening amenities).

patenting outcomes. Failure of these conditions would again lead to biased estimates. For example, national technology trends may be correlated with H-1B policy adjustments, and the former can independently produce employment differences across cities if technology compositions closely align with cities' H-1B dependencies. Alternatively, the interaction will not overcome the endogeneity problem if very dependent firms and cities influence the size of the program established by the federal government through lobbying or similar activities (e.g., Reksulak et al. 2006, Facchini et al. 2008). Our empirical analysis will thus test for these issues.

We now describe more closely the two elements of the interaction. The interaction term does not recover the true $\tilde{\beta}$ coefficient of interest, and we must carefully define the variables to provide scale and intuition for the results. First, H-1B$_t$ is Lowell's measure of the visa-holding population. We lag the years shown in Figure 2.4 by one year to align USCIS fiscal years with calendar years. Before interacting, logarithms of H-1B$_t$ are taken to remove scale dependency. Second, we develop two estimates of H-1B$_c$, which are described shortly. We normalize each of these dependency measures to have unit standard deviation before interacting.

Our first measure of a city's H-1B dependency is derived from the DOL microdata on LCAs. This measure is constructed as the yearly average of the city's LCAs in 2001-2002 normalized by the city population. There are several advantages of this metric. First, it is very closely tied to the H-1B program and can be measured for all cities. Second, the metric can be extended to the firm level, a disaggregation that we exploit in Section 2.5. Finally, LCAs measure latent demand for H-1B visas; demand is measured independent of whether an H-1B visa is ultimately realized or not. Moreover, measured demand is real in that non-trivial application and legal costs exist, and firms must list individual candidates on accompanying documents.

These strengths of the LCA-based dependency make it our preferred metric, but it does have important weaknesses. Our primary concern is that the dependency is measured at a mid-point during the sample period, rather than in a pre-period. To the extent that cities endogenously develop stronger attachment to the H-1B program, our measured dependency is not really fixed cross-sectionally and will lead to upwardly biased treatment effects. Second, the LCA data also have some noise in actual H-1B visa placement. While the H-1B visa is granted for a specific worker and a specific location, one of the most common abuses of the program is for firms to shift workers illegally to other locations. A 2008 USCIS investigation found violations of this nature in 11% of sampled H-1B cases (compared to 6% of cases where the prevailing wage was not being paid). This measurement error will tend to bias treatment effects downward.[15]

Given these weaknesses of the LCA metric, our second measure of H-1B$_c$ is the 1990 count of non-citizen immigrant scientists and engineers in the city with bachelor's educations or above, again normalized by city population. This metric is calculated from the 1990 Census of Populations and is much more conservative, being entirely measured before the 1990s growth in SE immigration evident in Figures 2.1-2.3. This measure also has the nice advantage of allowing contrasts with Canadian cities that we exploit below. It is very closely related to the measures used in Card (2001) and Hunt and Gauthier-Loiselle (2008), albeit with a focus on local SE employment. Its primary disadvantage is that the non-citizen immigrant category includes permanent residents and other temporary workers besides H-1B

[15]Overall, the 2008 USCIS study found fraud or technical violations in 20% of sampled H-1B cases, with incident rates especially high among small employers and business services firms (e.g., accounting, human resources, sales).

holders (e.g., exchange visitors, students). Measurement error in the regressor of this form will bias elasticity estimates downward from their true treatment effects.

Tables 2.1 and 2.2 document the most dependent cities and states. A number of big cities are dependent upon the H-1B program, which is similar to other immigration clustering, but many smaller cities are influenced as well. San Francisco is the most dependent city in the LCA-based ranking. In the Census-based ranking, Lafayette-West Lafayette, IN, and Bryan-College Station, TX, are ranked higher than San Francisco. These cities are home to Purdue University and Texas A&M University, respectively, and their surrounding SE industries. Other heavily dependent cities include Raleigh-Durham, Boston, and Washington, although considerable variation exists outside of the top rankings. The least dependent cities are Pascagoula, MS, and Rapid City, SD, according to the LCA and Census metrics, respectively. The bottom 40% of cities includes 16 cities with populations in 1994 greater than half a million. Prominent examples are San Antonio, TX, Tampa-St. Petersburg, FL, Providence, RI, and Norfolk-VA Beach, VA. The pairwise correlation of the two rankings is 0.5 across all cities.

We now return to the definition of cities as the relevant market for these effects. The appropriate market definition should reflect the speeds of SE labor, product, and technology flows. While the SE market is national in scope in the long-run, we believe that cities are an appropriate choice for a short-run analysis given the location-specific nature of H-1B visas, local labor mobility, and short-run rigidities in firm location choices.[16] We generally prefer cities to states as economic units in this context, although data limitations require us to study the latter when using

[16] Agglomeration studies typically identify cities and commuting regions as the relevant spatial unit for labor market effects on firms, and technology spillovers are found to operate at even shorter distances. For example, Rosenthal and Strange (2001), Ellison et al. (2009), and Glaeser and Kerr (2009).

the CPS. For example, a state-level dependency for North Carolina would mask substantial differences between Raleigh-Durham and Wilmington, among the most and least H-1B dependent cities nationally. From an econometric perspective, city-level granularity also allows for stronger regional trends and controls. We further exploit some sector-level variation in robustness checks and our firm-level analyses.[17]

These decisions may influence our measured treatment effects. For many variables, we would anticipate a positive β coefficient regardless of the variation exploited. For example, one would anticipate that localized growth in H-1B populations would increase employment of temporary immigrant scientists and engineers or patents by Indian and Chinese inventors whether looking across cities, industries, or occupations. Of course, the magnitudes of these effects are unknown and important to assess.

For effects on natives, however, even the sign of the β coefficient is unclear as immigrants may substitute or complement native workers. A negative coefficient would suggest that natives are crowded-out of SE employment or patenting by H-1B workers, either through direct replacement within firms or through worker choices (e.g., switching occupations due to lower salaries). On the other hand, crowding-in effects could exist. For example, employing immigrants with special SE skills may lead firms to devote more resources to R&D, thereby expanding employment and innovative activity for natives. Moreover, agglomeration economies may exist at the city level. If H-1B expansions lead to greater SE employment and innovation in an area, similar firms may benefit from locating nearby or expanding employment in local facilities. These agglomeration forces are particularly strong in innovative

[17]Borjas (2003) argues analyzing immigration through education-experience cells under the assumption of an otherwise national labor market. The H-1B program is almost entirely confined to workers with bachelor's education levels and above, limiting the effectiveness of this technique.

fields and are one of the central ways that the economics of high-skilled immigration may differ from low-skilled immigration.

Finally, it is important to stress that our empirical analysis of the H-1B program emphasizes short-term effects. Several channels through which immigrant scientists and engineers may impact the US economy operate over longer horizons than the panel considered (e.g., adjusting college major choices for natives, immigrants starting entrepreneurial firms). These effects may lead to long-run effects that differ from our work.

2.4.2 CPS State-Level Employment Outcomes

Our first analysis considers employment outcomes in the CPS at the state level over the 1995-2008 period. This analysis is a nice starting point as employment and wage patterns most directly relate to the theoretical framework outlined above and are themselves a central policy concern. Since 1994, the CPS has identified whether respondents are non-citizen immigrants, citizen immigrants, or US natives. This reporting of immigration status is also an important complement to our patenting analysis where immigration status is inferred.

The CPS, however, also brings substantial liabilities. Most importantly, the CPS is designed as a representative sample for the US, not for small geographic areas like cities and states. As a consequence, immigrant SE records are incomplete for a quarter of potential state-year observations. Even for complete series, small sample sizes also result in substantial measurement error. Second, the CPS redesign in 2003 creates a structural break in variable definitions between 2002 and 2003. As a consequence, we employ a first-differenced version of specification (2.2) that drops

2002-2003 changes. This dropped year is an important inflection point for the H-1B program, but we unfortunately cannot separate economic changes from survey coding changes.[18]

Regressions are unweighted and cluster standard errors at the cross-sectional level by state; we discuss our clustering choices further in the city analysis below. In addition to year fixed effects, we also control for contemporaneous changes in state labor market conditions with several unreported controls. These controls help isolate the impact of the H-1B program from unmodeled factors specific to states and from CPS variable redefinitions.[19]

Table 2.3 presents our first set of CPS results with Panels A and B utilizing LCA-based and Census-based dependencies, respectively. Column 1 finds growth in non-citizen immigrant scientists and engineers with higher H-1B admission rates. A 10% growth in the national H-1B population corresponded with a 3%-4% higher growth in non-citizen immigrant SE employment for each standard deviation increase in state dependency. The β estimates are statistically precise and economically meaningful in size. Moreover, the 10% increase discussed is realistic as the average annual increase in the H-1B population during the sample period is 7%.

Column 2 finds a weaker elasticity for employment growth of all immigrant SE workers, which is to be expected. Column 3 finds very limited effects on native SE workers. The point estimates suggest a growth of 0.1%-0.4% with a 10% increase in the H-1B population, but these estimates are not statistically different from no

[18]Crossing 51 states/DC and 14 years yields 663 potential observations, but these data limitations result in 495 observations per regression. While the resulting panel is unbalanced, we find similar results when keeping just the 26 states that have full employment history for all SE categories.

[19]The state-level controls are log population, log income per capita, log workforce size, the overall labor force participation rate among worker age groups, the overall unemployment rate, and the overall mean log weekly wage for full-time male workers with bachelor's educations or higher. We construct the latter four controls to mirror the SE outcome variables in Tables 2.3 and 2.4. This helps to ensure our robustness to general changes in CPS sampling frames or variable definitions, although similar results are found without these controls.

effect at all. In aggregate, Column 4 suggests a 0.3%-0.6% growth in the total SE workforce following a 10% growth in the national H-1B population per standard deviation increase in state dependency. The 0.6% outcome with the LCA-based measure is statistically significant, while the Census-based elasticity is not.[20]

The three columns in Table 2.4 consider other outcome measures for native SE workers with bachelor's educations and higher: labor force participation rates, unemployment rates, and mean weekly wages. We present a battery of measures as effects for natives may come through different forms (e.g., unemployment rates may be misleading in this context to the extent that natives are pushed into part-time work). The point estimate with LCA-based dependency suggests a 1% decline in native SE weekly wages, but this effect is not statistically significant. The remaining outcomes further reinforce the conclusion that native SE workers are not strongly affected.[21]

2.4.3 City-Level Patenting Outcomes

Tables 2.5 and 2.6 present our city-level patenting results using the LCA-based and Census-based dependencies, respectively. Estimations consider 281 cities over 1995-2007 for a total of 3653 observations. Column headers indicate dependent variables. We test for effects on the log level of city patenting for four ethnic groups in separate

[20] Unreported elasticities for citizen immigrant SE employment are 0.131 (0.091) and 0.044 (0.133) with the LCA and Census dependencies, respectively. These elasticities confirm the concentrated impact of the H-1B reduced-form interaction on its primary population. They also suggest that previous immigrant SE workers are not being displaced by H-1B workers.

[21] Having viewed these results, we can comment further on our reduced-form estimation design. It was earlier mentioned that the reported β coefficients do not recover the $\tilde{\beta}$ parameter from specification (2.1). Estimating this parameter would be advantageous and is the rationale for implementing a two-stage least squares (2SLS) model. In our patenting analyses, this is not feasible as we do not observe the endogenous regressor (i.e., H-1B$_{c,t}$) by city or firm. A 2SLS model would potentially be feasible in Tables 2.3 and 2.4 if we made the endogenous regressor the broader non-citizen immigrant SE population. The coefficients in Column 1 of Table 2.3 would be the first-stage estimations, and the rest of the estimations in Tables 2.3 and 2.4 would be the reduced-form outcomes. The evident statistical power of both these components, however, shows that the resulting two-stage model would be imprecisely estimated.

regressions: Indian, Chinese, Anglo-Saxon, and Other Ethnicity inventors. Other Ethnicity inventors include European, Hispanic, Japanese, Korean, Russian, and Vietnamese contributions. The fifth column considers log total patenting in the city.

Regressions again cluster standard errors cross-sectionally, this time by city. As our interaction term additionally relies on common annual variation from changes in H-1B populations, we also tested clustering by year. These standard errors are substantially smaller than clustering cross-sectionally, and so we take the more conservative approach. We further tested the two-way clustering technique of Cameron et al. (2006), which returns results very similar to cross-sectional clustering.

The first column of Table 2.5 finds a positive relationship between increases in H-1B visa allocations and Indian patenting in dependent cities. A 10% increase in the H-1B population is associated with a 3% increase in Indian patenting for each standard deviation growth in city dependency. Column 2 finds a slightly stronger relationship for Chinese invention. These elasticities are comparable to the CPS employment estimates for non-citizen immigrant SE workers in Table 2.3, a point to which we will return after viewing the full set of results.

Column 3 shows that the Other Ethnicity inventor group increases patenting in dependent cities, too. The elasticities, however, are less than half of the magnitude for Indian and Chinese inventors in Columns 1 and 2, and the linear differences are statistically significant. This confirms our expectations about the distribution of treatment effects of the H-1B program across different immigrant groups. Column 4 further finds that growth in inventors with Anglo-Saxon names in dependent cities is weakly responsive to shifts in H-1B admissions. We estimate that a 10% increase in the H-1B population is associated with a 0.5% increase in Anglo-Saxon invention per standard deviation of city dependency. This elasticity is about a seventh of the magnitude estimated for Indian and Chinese inventors.

The final column finds a positive effect for total patenting. The weaker effect for total invention compared to Columns 1 and 2 is to be expected given that Indian and Chinese inventors comprise less than 15% of US domestic patenting during the period studied. The estimates suggest that a 10% growth in the H-1B worker population is associated with a 0.7% increase in patenting per standard deviation of dependency. This elasticity is again comparable to the CPS estimate for the total SE employment growth by state.

The first row of Table 2.6 repeats this analysis with the Census-based dependency. The overall picture remains the same, especially the ordering across ethnicities. Elasticities with the Census-based dependency are smaller for all ethnicities, likely due to both a more conservative approach and greater measurement error in the estimated dependencies. This closely parallels the differences between Panels A and B of Tables 2.3 and 2.4. The results for the growth in Anglo-Saxon and total invention are smaller, a pattern more suggestive of the H-1B program not having any effect on native inventors and a weak total impact.

The similar pattern of spatial effects in the ethnic patenting data and the CPS are comforting from a methodological perspective, as the patent data allow many more extensions that we turn to next. This comparability, although perhaps initially surprising, is also to be expected upon further reflection. We earlier noted that immigrant scientists and engineers are of comparable quality to natives, with their disproportionate impact for US science and engineering coming primarily through their more extensive training and employment in SE fields. This comparability is particularly emphasized by Hunt (2009). The estimations in Tables 2.3-2.6 simply show that the larger populations of these immigrants following H-1B program expansions increase US invention through greater numbers of SE workers. To the extent that native scientists and engineers are not substantively affected by the program, total employment and invention also expand.

This perspective likewise addresses the fact that a substantial portion of H-1B visa holders are not engaged in patenting activities. Many H-1B workers, for example, are engaged in routine software coding and testing activities that do not result in patents. To this point, a number of H-1B holders are also engaged in very advanced tasks like specialized mathematics that are innovative but not patentable. This frequent engagement in efforts other than patenting is a significant aspect of H-1B employment, just as it is considerable among native SE workers. The program is important enough with respect to Indian and Chinese SE activity, however, that recent immigrants who do patent often hold an H-1B visa at some stage of the immigration process. These workers may be hired directly from abroad on an H-1B, or they may be transitioning from school to work within the US. Both paths require a visa and are subject to the cap. Thus, increases in this overall population of immigrant SE workers can yield expansions of US invention and SE employment without the H-1B program specifically targeting patenting.[22]

[22] Perhaps the more surprising finding is the comparable elasticities for Indian and Chinese invention. Even after considering Taiwan, Singapore, and related economies, the H-1B inflow of Chinese ethnicity SE workers is smaller relative to the overall population of Chinese inventors in the US than for Indian invention. Several factors likely lead to more equal elasticities, including a weaker propensity among marginal Indian H-1B holders to engage in patenting compared to Chinese holders. These results also might reflect crowding-in effects for other Chinese inventors. We find evidence for this latter effect in expansions of Chinese invention around technologies initially dominated by Indian inventors.

2.4.4 City-Level Robustness Analysis

The remainder of Tables 2.5 and 2.6 present robustness checks on these basic findings. The linear framework (2.2) provides a parsimonious specification, but it is useful to examine effects throughout the dependency distribution. To do so, we first group cities into five quintiles of dependency, with each quintile containing 56 or 57 cities. We then generate three indicator variables (with notation $I_c(\cdot)$) for whether city c is in the 3rd, 2nd, or most dependent quintiles of H-1B dependency. The bottom two quintiles, which account for 40% of US cities but only 1% of LCA applications, serve as the reference group for measuring the effects on the top three quintiles.

Our extended estimating equation is

$$\begin{aligned}\ln(PAT_{c,t}) \quad = \quad & \phi_c + \eta_t \\ & +\beta_1 \cdot [I_c(\text{Top Quintile}) \cdot \ln(\text{H-1B}_t)] \\ & +\beta_2 \cdot [I_c(\text{2nd Quintile}) \cdot \ln(\text{H-1B}_t)] \\ & +\beta_3 \cdot [I_c(\text{3rd Quintile}) \cdot \ln(\text{H-1B}_t)] + \epsilon_{c,t}.\end{aligned} \tag{2.3}$$

This flexible specification again tests whether innovation patterns in cities thought to be dependent upon H-1B workers are more or less sensitive to changes in H-1B population levels. Considering the top three quintiles separately allows us to test for non-linear effects in the city distribution. The quintiles framework also tests whether our results are sensitive to the scale through which H-1B dependency is measured, as only the ordinal ranking of cities is used for grouping them. Said differently, in this approach we constrain the effects to be similar within the quintiles in specification (2.3). Main effects are again absorbed into the panel fixed effects.

Panel B of Tables 2.5 and 2.6 provide a consistent picture of treatment effects that grow with dependency. They suggest that the linear approach is not identifying off of the most extreme cases. They also provide assurance that the results are not being biased by a small group of cities or firms that exerts a substantial impact on admissions decisions and likewise receives disproportionate benefits. Effects are clearly strongest in the most dependent quintile, but the pattern of results looks similar in the second and third quintiles that we expect to have very little or no influence on H-1B admission choices. LCA applications are significantly skewed toward the upper quintile, suggesting that this is where the vast majority of political influence comes from. This is comforting as the evolution of the H-1B program can reasonably be taken as exogenous outside of the top cities.

These quintile estimations also allow a second interpretation of the economic magnitudes of the results. A 10% growth in the national H-1B population is associated with a 6%-12% growth in Indian and Chinese patenting in cities within the most dependent quintile relative to the control group. The corresponding impact for total invention is 0%-2%. The growth effect in the second and third quintiles is 3%-8% for Indian and Chinese patenting, with total invention expanding by 1% or less.

Panel C returns to the linear specification to test controlling for additional labor market characteristics. It is natural to worry whether the reduced-form interactions in (2.2) are capturing other heterogeneity across cities than H-1B dependency or other time effects than the aggregate shifts in H-1B admissions. The ordering of elasticities across ethnicities provides helpful assurance in the story presented, as other explanations must similarly explain localized treatment effects among Indian and Chinese inventors.

Panel C incorporates more explicit controls. Analogous to Table 2.3, we first include the log of the population and income per capita of the city as regressors. We also include region-year fixed effects to control for broader trend differences across the nine Census regions since 1995. These regional controls are easily extended to state-year fixed effects, but the broader groupings provide a more consistent number of cities per grouping. Finally, Figures 2.2 and 2.3 highlight that Indian and Chinese inventors are more concentrated in high-tech sectors than other ethnic groups. Differences in sectoral growth rates or changing propensities to seek patents may consequently impact our findings. We thus include measures of expected city-level patenting for each ethnic inventor group based on national patenting trends and pre-period city technology specializations.[23]

When we introduce these strict controls, the relative ordering of treatment effects remains the same as in Panel A. The elasticities uniformly decrease in economic magnitude, while the standard errors remain constant. These estimates find that a 10% increase in the H-1B population increased Indian and Chinese invention by 1%-2% per standard deviation of dependency. Effects for Anglo-Saxon inventors are not statistically different from zero for either dependency measure, while total invention is estimated to have increased by about 0.5% per standard deviation of dependency.

Continuing with this extended regression, Panel D excludes from the sample patents related to Computers and Communications (USPTO category 2). The H-

[23]We construct our expected patenting measures by first calculating the mean annual patenting done in the focal city by each ethnic group over 1990-1995 in 36 technology sectors. These sectors are the sub-categories of patent classifications; examples include “Resins”, “Computer Peripherals”, and “Optics.” We then take subsequent growth in national patenting for each sector, weight these trends by the city’s pre-period composition, and sum across technologies. To maintain a consistent specification and to maximize explanatory power, we include the expected patenting trends for all four ethnic groups in each estimation. Each ethnicity is particularly dependent on the expected trend for its own ethnicity. Chinese inventors also experience large increases in cities with strong expected Indian patenting growth in the IT sector.

1B program is closely linked to the development of the IT sector and grew strongly during the 1990s high-tech boom period. Beyond the expected technology trends included in Panel C, this regression further tests whether patents from the computer sector and neighboring fields are solely driving the observed relationships. Although the coefficient estimates are somewhat smaller, the qualitative findings are in general quite comparable.

Our earlier working paper reports a number of additional robustness checks. We first substitute a six-year summation of the annual H-1B visa cap in place of Lowell's H-1B population estimates for H-1B$_t$. The cap summation introduces more measurement error into the H-1B population estimate, but it perhaps benefits from stronger exogeneity. The results are very similar with this alternative estimation, since the cap has been binding or close to binding in most years. Generally, the modelling choice of H-1B$_t$ is of second-order importance to the dependency measure employed for cities.

Comparable results are also found when excluding the West Coast, when testing before and after 2001, and when excluding recent patent applications. We find similar effects when using first-differenced specifications, although autoregressive tests of error terms suggest that levels specifications are more appropriate. Importantly, the findings also hold when introducing additional interaction terms focused on city populations or growth in US citizen immigrant SEs. Our main estimations recode counts of less than one ethnic patent for a given city-year observation to be equal to one ethnic patent. We do so under the claim that is not meaningful to distinguish between zero and one Indian or Chinese patent for a city. This is merely done to maintain consistent sample sizes, and the elasticity estimates are similar when we instead exclude zero-valued cells.

We further performed estimations that drop all patents associated with 307 of the most highly-dependent firms that we could identify. These firms account for 30% of patents during 1995-2006 and are discussed in more detail in Section 2.5. This grouping includes the most frequent LCA applicants and the largest US patentors. Our results are robust to this technique, confirming that the important effects estimated for the second quintile are not due to a few influential firms patenting in several cities. We also find similar coefficients for the top quintile when dropping the 20 most dependent cities of this group, suggesting again that the results extend deeper than the extreme cases like San Francisco and Boston.

One limitation of our approach, however, is important to note. Our econometric specifications are motivated by empirical studies finding that contemporaneous R&D investments have the most important impact for rates of technology formation (e.g., Pakes and Griliches 1980, Hausman et al. 1984, Hall et al. 1986). In the context of this chapter, we consider how recent investments in hiring high-skilled immigrants affect innovation. When looking at dynamic specifications that introduce leads and lags on the observed H-1B population, however, the patterns are mixed. We often find contemporaneous effects to be the most important, but the patterns are unfortunately too sensitive to specification choices or included time periods to draw conclusions. Thus, while our interaction approach can measure cross-sectional sensitivity to longitudinal program changes, it cannot identify the precise timing from H-1B population adjustments to patenting outcomes.[24]

[24]These lag structure limitations are due to both data constraints and economic reasons. Perhaps the most important issue is a shift in occupations using H-1B visas that occurred in the mid 1990s (e.g., Hira 2004). The share of H-1B visas granted to healthcare and therapy occupations declined from 54% in 1995 to 14% in 1998. SE and computer specialist occupations grew from 25% to about 60% during this same period, and the SE sector has been dominant since this inversion. Our main estimations are robust to whether we use Lowell's total H-1B populations, six-year summations of the H-1B cap, or attempt to adjust for occupational shifts. These modelling

2.4.5 Comparison to Canadian Cities

Canadian cities provide a useful baseline for comparing the estimated effects of the H-1B program on US ethnic invention patterns. Indian and Chinese inventors account for about 15% of Canada's patents during the 1995-2007 period, only slightly more than in the US, and the technology breakdowns are similar for the two countries. We therefore test whether Canadian cities display similar or different trends in innovation relative to those found in the US. Identical trends in Canada and America would warn that our estimates are biased by other secular changes (e.g., greater Indian and Chinese immigration to North America interacting with past immigrant networks).

Many Canadian inventors seek patent protection from the USPTO. Using over 200,000 granted patents and non-overlapping applications filed from Canada, we estimate the ethnic composition of Canadian inventors in metropolitan areas that are comparable in size and scope to the US Metropolitan Statistical Areas through which we define US cities. Likewise, we use the 1991 Canadian Census of Populations (IPUMS) to construct non-citizen immigrant SE dependency metrics roughly similar to our Census-based metrics for the US. We are able to construct city-level dependencies for 22 cities, with Toronto and Vancouver being the most dependent major Canadian cities. We unfortunately do not have an equivalent to the LCA data set for Canada.

Panel E of Table 2.6 presents the placebo experiment using the Canadian sample of cities. We regress ethnic patenting in Canadian cities against each city's non-citizen immigrant SE dependency interacted with the log of the US H-1B population. As

choices, however, can substantively influence lag structure analyses.

in Panel A, these regressions include city and year fixed effects. None of the results are significantly different than zero, and the point estimates are small in economic magnitude. Extensions of this placebo analysis, such as estimating a variant of specification (2.3), find similar results.

The null results are reassuring for our empirical design. They suggest that our findings for the US are not being driven by unmodeled secular changes that also impacted Canada. Such secular trends could include, for example, globalization and the rapid economic development of India and China. As the technology fields of Indian and Chinese inventors are similar in Canada and America, many industry cycles are also captured. Of course, this Canadian analysis will not capture unmodeled secular trends exclusive to the US.

2.5 Firm-Level Analayses of the H-1B Program

We extend our city-level results with a firm-level analysis that exploits additional detail that is possible with the ethnic patenting data. Substantial heterogeneity exists across firms in ethnic invention, and this variation allows us to characterize the impacts of H-1B visa changes in an alternative way. This is the first large scale description of ethnic invention within firms and the first analysis of the link between immigration and innovation at the firm level of which we are aware. We focus on 77 major patenting firms that are likely to be influenced by high-skilled immigration. These firms are all publicly listed, headquartered in the US, have at least four patents per year, and have measurable ethnic patenting. They account for a quarter of all US patenting during the 1995-2007 period.[25]

[25] Our sample construction involved two steps. We first identified 592 unique firms that met one of three criteria: (1) firms included in two lists of top H-1B sponsors for 1999 and 2006 (the only two lists for our sample period); (2) firms accounting for 0.05% or more of patent grants or applications during 2001-2004; and (3) firms accounting for 0.03% or more of LCA applications during 2001-2006. Of these 592 firms, 307 have at least one patent during the

Table 2.7 details the general characteristics of this sample. The firms have over 345 patents on average per year, and the ethnicity and geography of inventors in these firms broadly match US aggregates. A comparison of the means and medians across these different technology categories and regions also demonstrates that firms tend to specialize in particular types of innovation and to spatially cluster their innovations. Although sampled firms are generally quite large, substantial variation exists in sales, employees, R&D expenditures, and LCA applications. Unreported regressions find that larger firms and high-tech firms tend to have higher shares of Indian and Chinese inventors. Firms undertaking most of their innovative activity in the Middle Atlantic and West Coast regions also have higher average shares of ethnic inventors. Among these employers, technology focus and regional location explain more of the variation in ethnic inventor compositions than firm size.

In order to understand the effects of different admissions levels on firms, we consider a specification similar to the linear approach (2.2) employed in the city analysis. We measure H-1B dependency through each firm's 2001-2002 LCA filings normalized by Compustat employment. We again interact this dependency with the national H-1B population estimate. Regressions include panel fixed effects and cluster standard errors cross-sectionally by firm.

Table 2.8 presents the firm-level findings. Panel A finds that ethnic invention, and Indian invention in particular, is closely tied to H-1B admissions levels. A 10% growth in H-1B admissions correlates with an 4%-5% growth in Indian invention for each standard deviation increase in dependency. The program is linked to a 3% higher growth in total invention per standard deviation increase in dependency.

sample period. We then made additional restrictions on the firm being publicly listed and having ethnic patenting in each year to facilitate an intensive margin analysis of patenting. We find similar results when using an unbalanced panel built off of the larger sample. We document the sample construction in extensive detail in our earlier working paper.

These results point to particularly powerful impacts for heavily influenced firms among major patenting firms.

Panel B extends the estimation to include a firm-specific measure of expected patenting. This measure is based on pre-period technology specializations and national patenting trends. Unlike before, however, we do not construct ethnic-specific technology trends given the limited pre-period data for many firms. We also include region-sector-year fixed effects. We define regions through the four Census regions and sectors through patent categories. On both dimensions, firms are classified by where they patent the most during the sample period. These fixed effects remove annual trends common to a sector and region, such as the growth of the computer-oriented sector on the West Coast. The patterns are very similar in this extended regression.

Panel C finally tests for heightened sensitivity in the computer-oriented sector where the H-1B program has been very influential. Continuing with the extended specification in Panel B, we interact the core regressor with an indicator variable for the computer and communications patent category. We demean both regressors before interaction to restore main effects, and the main effect for the computer-oriented sector is absorbed by the region-sector-year fixed effects. The base effects find a similar pattern excepting the weaker role of Chinese inventors. The interactions suggest that Indian and Chinese responses are particularly strong in the computer-oriented sector.

We consider this firm-level analysis as a nice robustness check on the city-level and state-level approaches. It provides microeconomic evidence in support of the labor market results, and it quantifies the claims of high-tech executives that their firms are especially vulnerable to high-skilled immigration policies for temporary workers. As some of our 77 firms are among the primary lobbyists for H-1B legislation, however, these results should be interpreted as partial correlations only.

2.6 Conclusion

Over the last fifteen years, the H-1B visa program for temporary workers has played a significant role in US innovation. As immigrants are especially important for US innovation and technology commercialization, this makes the H-1B program a matter of significant policy importance. We find that fluctuations in H-1B admissions significantly influenced the rate of Indian and Chinese patenting in cities and firms dependent upon the program relative to their peers. Most specifications find limited effects for native SE employment or patenting. We are able to rule out displacement effects, and small crowding-in effects may exist. We conclude that total invention increased with higher admissions primarily through the direct contributions of immigrant inventors.

We close with four related research questions that we hope can be addressed in future work. First, we have focused exclusively on the H-1B program given its particular importance in science and engineering and large admissions fluctuations. We hope that future research will consider other temporary visa categories. The H-1B program has unique characteristics, and quantifying the impacts of other visa programs will clarify whether our results apply generally or are due to particular features of the H-1B program. For example, the prevailing wage requirement may limit adverse effects for natives to the extent that the requirement is followed. Likewise, the manner in which H-1B workers are tied to their sponsoring firms may produce special outcomes. Such comparative assessments will also aid policy makers when crafting future immigration policies.

Second, our analysis considers high-frequency variation since 1995, and we cannot quantify long-run impacts of these policy choices as a consequence. Given the time and expense involved in training new SE workers, long-run effects may be different. Fluctuations in the H-1B cap are quite recent, so researchers will need to unite our work with studies exploiting low-frequency variation to understand these dynamics. It is also important for future research to extend beyond area-based studies to analyze variations across alternative dimensions like occupations and industries. These complementary approaches will help assess likely effects at the national level and would further inform future theoretical work on how the supply side of innovation influences overall US technology growth.[26]

Third, our analysis quantifies patenting growth due to higher H-1B admission rates for cities and firms. There are many different types of research organizations: universities, government labs, private inventors, and others. We have not analyzed how changes in the H-1B program alter the local relationships among these different institutions. For example, the comparative advantage that universities have had for obtaining H-1B visas since 2001 may result in greater dependencies of local industry on universities for certain forms of SE advancement. Understanding these local inter-linkages will be informative for both H-1B program assessments and of general interest for technology transfer studies.

Finally, although ethnic patenting data allows us to characterize the role of H-1B workers for US innovation and SE employment in a unique way, we recognize that the H-1B program impacts other aspects of the US economy. About half of the

[26] We earlier noted general mechanisms that are likely to exist regardless of approach (e.g., increased supply of knowledge, complementarities). We also noted that agglomeration economies are likely to play an important role in spatial analyses. Future work should evaluate whether relevant agglomeration economies are stronger or weaker at the national level. Some agglomeration rationales like labor pooling would suggest that city-level effects would be stronger. We note, however, that current concerns over higher rates of return SE migration to India and China focus on a loss of US technology leadership. The fear is less about losing individual scientists than losing the critical mass of frontier scientists, a process that would depend upon significant country-level agglomeration economies.

major employers of H-1B visas that we identified for potential inclusion in our firm sample did not file for a patent during our period of study. Future research should quantify the economic impacts for other sectors like accounting and consulting firms, banks and financial institutions, and public services in ways that are appropriate for these sectors. It will likewise be particularly interesting to quantify job creation or displacement effects for occupations other than inventors among high-tech firms.

2.7 Tables and Figures

Table 2.1: Most Dependent Cities on the H-1B Visa Program

	LCA-Based Dependency: 2001-2002 LCA Filings per Capita (x 1,000) (1)		Census Dependency: 1990 Noncitizen Immigr. SE Workforce per Capita (x 1,000) (2)	
1	San Francisco, CA	8.323	Lafayette-W. Lafayette, IN	7.810
2	Miami, FL	5.502	Bryan-College St., TX	5.571
3	Washington, DC	5.430	San Francisco, CA	5.096
4	Raleigh-Durham, NC	5.220	Columbia, MO	4.462
5	Boston, MA	5.149	Gainesville, FL	4.146
6	Austin, TX	4.897	Champ.-Urbana-Rant., IL	4.023
7	New York, NY	4.777	Washington, DC	3.168
8	Burlington, VT	4.491	Boston, MA	3.129
9	Atlanta, GA	4.116	Raleigh-Durham, NC	2.723
10	Dallas-Fort Worth, TX	3.943	Los Angeles, CA	2.288
11	Champ.-Urbana-Rant., IL	3.819	Rochester, MN	2.247
12	Iowa City, IA	3.804	New York, NY	2.185
13	Houston, TX	3.712	Houston, TX	2.156
14	Bryan-College St., TX	3.577	Spokane, WA	2.078
15	Seattle, WA	3.393	State College, PA	2.058

Notes: The table presents largest dependencies on the H-1B program by city. Dependency in Column 1 is measured as the sum of Labor Condition Applications (LCAs) over 2001–2 normalized by population. These applications are an initial step for obtaining an H-1B visa. Dependency in Column 2 is measured as noncitizen scientists and engineers per capita in the 1990 census. Noncitizens include temporary visa holders (e.g., H-1B) and permanent residents. Both dependencies are multiplied by 1,000 for presentation purposes. Washington, DC, in panel A differs from the District of Columbia in panel B, as the former includes metropolitan areas in Virginia and Maryland.

Table 2.2: Most Dependent States on the H-1B Visa Program

	LCA-Based Dependency: 2001-2002 LCA Filings per Capita (x 1,000) (1)		Census Dependency: 1990 Noncitizen Immigr. SE Workforce per Capita (x 1,000) (2)	
1	District of Columbia	9.829	New Jersey	2.491
2	New Jersey	4.013	California	2.455
3	Massachusetts	4.005	Massachusetts	2.056
4	California	3.502	District of Columbia	2.012
5	New York	3.366	Maryland	1.884
6	Connecticut	2.804	New York	1.485
7	Delaware	2.526	Delaware	1.395
8	Maryland	2.277	Connecticut	1.092
9	Florida	2.183	Texas	1.047
10	Texas	2.116	Virginia	1.014
11	Virginia	2.113	Michigan	.976
12	Georgia	1.974	New Hampshire	.967
13	Washington	1.937	Illinois	.963
14	Illinois	1.868	Washington	.890
15	Michigan	1.673	Hawaii	.832

Notes: See Table 2.1. Here we present similar figures by state.

Table 2.3: State-Year Regressions of H-1B Program Dependency and Science and Engineering Employment

	(1)	(2)	(3)	(4)
	A. LCA-Based Dependency			
Δ Log H-1B Population x	.385	.200	.037	.062
State Dependency	(.062)	(.067)	(.025)	(.023)
	B. Census Based Dependency			
Δ Log H-1B Population x	.270	.150	.010	.034
State Dependency	(.151)	(.107)	(.036)	(.038)

Notes: State-year regressions estimate the effect of changes in the national H-1B population over 1995–2008 for science and engineering (SE) workforces by state using the Current Population Survey (CPS). The dependent variable differs for each column. In order, they are (1) Δ log noncitizen immigrant SE workers (2) Δ log immigrant SE workers (3) Δ log native SE workers and (4) Δ log total SE workers. The annual H-1B population regressor is interacted with state-level dependencies. Dependency in panel A is measured through LCA applications in 2001–2 divided by state populations. Dependency in panel B is measured through noncitizen immigrant SE workforces in the 1990 census divided by state populations. Dependencies are normalized to have unit standard deviation before interacting. First-differenced specifications are utilized due to the redesign of the CPS in 2003; changes from 2002–3 are excluded. The CPS sample is restricted to state-years where changes in all outcome variables from the prior year are observed, for a total of 495 observations in each regression. The text describes the sample composition further. Regressions are unweighted and cluster standard errors by state. Regressions include year fixed effects and control for contemporaneous changes in log state population, log state workforce, overall state labor force participation rate among worker age groups, overall state unemployment rate, log state income per capita, and overall mean log weekly wage for full-time male workers with bachelor's educations or higher in the state. Similar results are found without these controls for contemporaneous changes in state labor market conditions.

Table 2.4: State-Year Regressions of H-1B Program Dependency and Science and Engineering Employment for Native SE Workers

	(1)	(2)	(3)
	A. LCA-Based Dependency		
Δ Log H-1B Population x	.004	-.002	-.010
State Dependency	(.004)	(.005)	(.013)
	B. Census Based Dependency		
Δ Log H-1B Population x	.005	.000	.003
State Dependency	(.006)	(.005)	(.018)

Notes: We perform similar estimations as those in Table 2.3, although only consider native SE workers for the estimations. The dependent variable differs for each column. In order, they are (1) Δ labor force participation (2) Δ unemployment rate (3) Δ mean log male weekly wage.

Table 2.5: City-Year Regressions of H-1B Program Dependency and US Invention

	Indian (1)	Chinese (2)	Other (3)	A-S (4)	Total (5)
	A. LCA-Based Dependency				
Log H-1B Population x City Dependency	.339 (.048)	.390 (.061)	.168 (.035)	.056 (.028)	.074 (.028)
	B. Quintiles Specification				
Log H-1B Population x (0,1) 3^{rd} Quintile	.357 (.096)	.343 (.098)	.219 (.108)	.053 (.106)	.071 (.106)
Log H-1B Population x (0,1) 2^{nd} Quintile	.661 (.089)	.833 (.106)	.382 (.088)	.116 (.089)	.125 (.084)
Log H-1B Population x (0,1) 1^{st} Quintile	.988 (.077)	1.208 (.092)	.507 (.088)	.180 (.090)	.227 (.089)
	C. Incl. Tech. Trends, Local Labor Conditions & Region-Year Effects				
Log H-1B Population x City Dependency	.142 (.045)	.174 (.061)	.056 (.034)	.023 (.029)	.048 (.029)
	D. Panel C Excluding Computer & Communications Patents				
Log H-1B Population x City Dependency	.132 (.045)	.160 (.059)	.051 (.035)	.020 (.029)	.038 (.029)

Notes: City-year regressions estimate the effect of changes in the national H-1B population over 1995–2007 for patenting by city. The dependent variable differs for each column. In order, they are (1) log Indian patenting (2) log Chinese patenting (3) log Other Ethnicity patenting (4) log Anglo-Saxon patenting (5) log total patenting. The annual national H-1B population regressor is interacted with the LCA-based city-level dependencies as defined in Table 2.1. Panels A, C, and D present linear specifications where dependencies are normalized to have unit standard deviation before interacting. Panel B groups cities into quintiles based upon dependencies. The annual H-1B population regressor is interacted with binary indicator variables for the top three dependency quintiles to measure effects relative to the bottom two quintiles. Regressions include city and year fixed effects, are unweighted, have 3,653 observations, and cluster standard errors by city. Panel C incorporates log expected patenting trends for each city-ethnicity, log city populations, log city mean income levels, and region-year fixed effects (nine census regions). Panel D further excludes patents from the computer sector (USPTO category 2).

Table 2.6: City-Year Regressions with Census Dependency and Canadian Placebo

	Indian (1)	Chinese (2)	Other (3)	A-S (4)	Total (5)
	A. Census-Based Dependency				
Log H-1B Population x City Dependency	.240	.291	.091	.014	.032
	(.031)	(.047)	(.029)	(.023)	(.023)
	B. Quintiles Specification				
Log H-1B Population x (0,1) 3^{rd} Quintile	.258	.584	.196	.042	.065
	(.111)	(.128)	(.103)	(.103)	(.103)
Log H-1B Population x (0,1) 2^{nd} Quintile	.444	.529	.232	.088	.092
	(.092)	(.119)	(.098)	(.103)	(.098)
Log H-1B Population x (0,1) 1^{st} Quintile	.570	.751	.125	-.012	.028
	(.100)	(.107)	(.098)	(.083)	(.085)
	C. Incl. Tech. Trends, Local Labor Conditions & Region-Year Effects				
Log H-1B Population x City Dependency	.084	.127	.043	.026	.045
	(.027)	(.039)	(.026)	(.023)	(.022)
	D. Panel C Excluding Computer & Communications Patents				
Log H-1B Population x City Dependency	.089	.107	.042	.020	.038
	(.026)	(.044)	(.030)	(.023)	(.024)
	E. Placebo w/Canadian City Sample				
Log H-1B Population x City Dependency	-.039	.097	.045	.015	.029
	(.065)	(.086)	(.048)	(.067)	(.055)

Notes: See Table 2.5. Panels A–D consider the census-based dependency of the city instead of using the LCA-based dependency. Panel E further considers a placebo experiment with Canadian cities for which pseudo-dependencies can be calculated from the 1991 Canadian census.

Table 2.7: Descriptive Statistics for Firm Panel

	Median	Mean	SD	Min.	Max.
	A. Firm-Level Patenting Composition (%)				
Indian inventors	6	8	5	1	32
Chinese inventors	9	10	6	2	28
Other ethnic inventors	22	22	4	9	43
Anglo-Saxon inventors	62	60	11	34	81
Chemicals	6	14	17	0	76
Comp. & Communications	16	28	29	0	99
Drugs & Medical	0	16	29	0	89
Electrical & Electronic	12	19	20	0	96
Mechanical	5	12	14	0	55
Miscellaneous	4	10	15	0	72
New England	2	6	14	0	93
Middle Atlantic	1	15	27	0	94
East North Central	1	19	31	0	97
West North Central	0	4	13	0	80
South Atlantic	2	7	15	0	84
East South Central	0	2	11	0	95
West South Central	1	10	23	0	98
Mountain	1	4	10	0	79
Pacific	10	32	38	0	98
	B. Firm-Level Activity				
Annual LCA Count	53	171	333	0	2,254
Annual Patent Count	167	345	499	42	3,501
Annual Sales ($m)	9,538	22,455	37,508	18	193,289
Annual Employees (k)	37	65	91	0	567
Annual R&D ($m)	519	1,224	1,637	17	8,413

Notes: Descriptive statistics for the 77 firms included in the firm panel for 1995–2007.

Table 2.8: Firm-Year Regressions of H-1B Program Dependency and US Invention

	Indian (1)	Chinese (2)	Other (3)	A-S (4)	Total (5)
	A. LCA-Based Dependency				
Log H-1B Population x Firm Dependency	.452	.315	.357	.256	.331
	(.120)	(.114)	(.080)	(.077)	(.077)
	B. Incl. Tech. Trends, Local Labor Conditions & Region-Year Effects				
Log H-1B Population x Firm Dependency	.497	.379	.370	.246	.335
	(.143)	(.153)	(.097)	(.106)	(.099)
	C. Panel B with Interaction for Computer Sector				
Log H-1B Population x Firm Dependency	.336	.144	.278	.149	.216
	(.170)	(.202)	(.106)	(.122)	(.120)
Log H-1B Population x Firm Dependency x (0,1) computer sector	.449	.656	.255	.271	.332
	(.262)	(.300)	(.174)	(.192)	(.181)

Notes: Firm-year regressions consider 1995–2007. All firm H-1B dependencies are constructed using our measure of LCA applications. The dependent variable differs for each column. In order, they are (1) log Indian patenting (2) log Chinese patenting (3) log Other Ethnicity patenting (4) log Anglo-Saxon patenting (5) log total patenting. Regressions include firm and year fixed effects, have 1,001 observations, are unweighted, and cluster standard errors by firm. Panel B incorporates expected technology trends for each firm and region-sector-year fixed effects. We define regions through the four census regions and sectors through patent categories. On both dimensions, firms are classified by where they patent the most during the sample period. Panel C further distinguishes effects within and outside of the computer sector. We interact the core regressor with an indicator variable for the computer and communications patent category. We demean both regressors before interaction to restore main effects, and the main effect for the computer-oriented sector is absorbed by the region-sector-year fixed effects.

Figure 2.1: Growth in US Ethnic Patenting

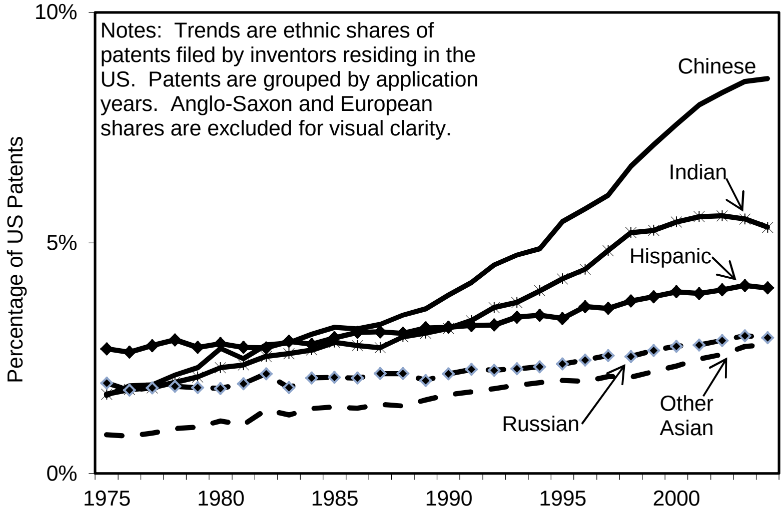


Figure 2.2: Indian Contributions by Technology

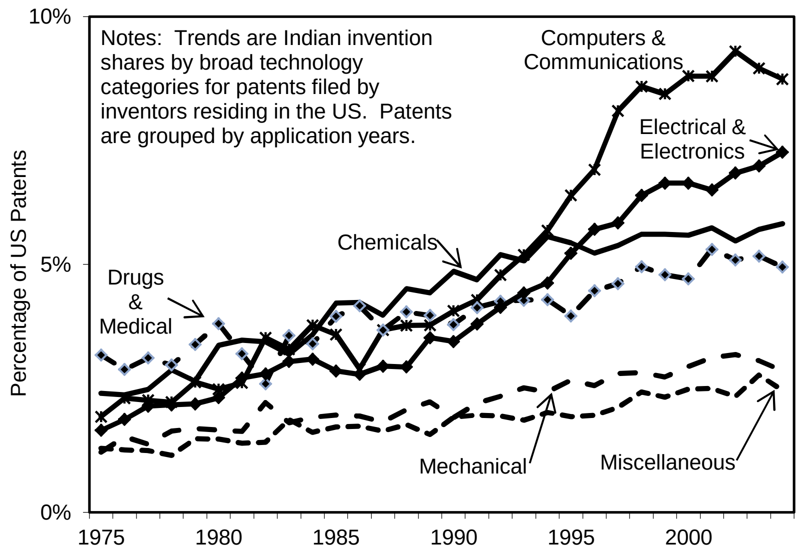


Figure 2.3: Chinese Contributions by Technology

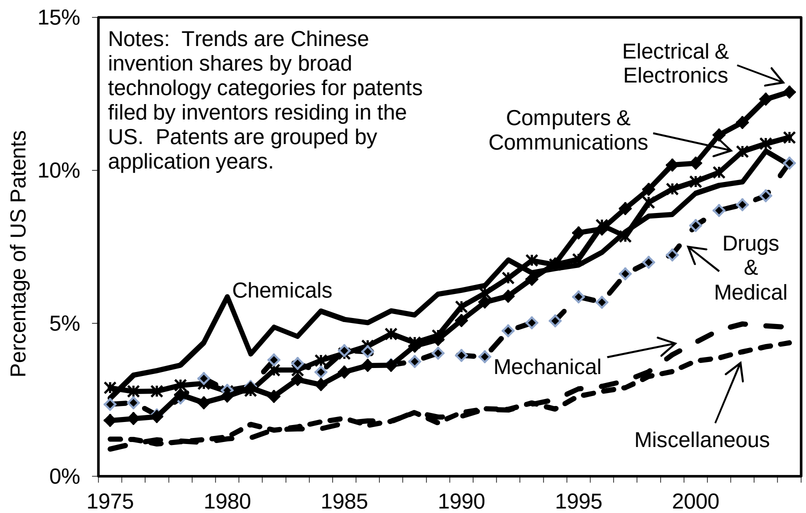
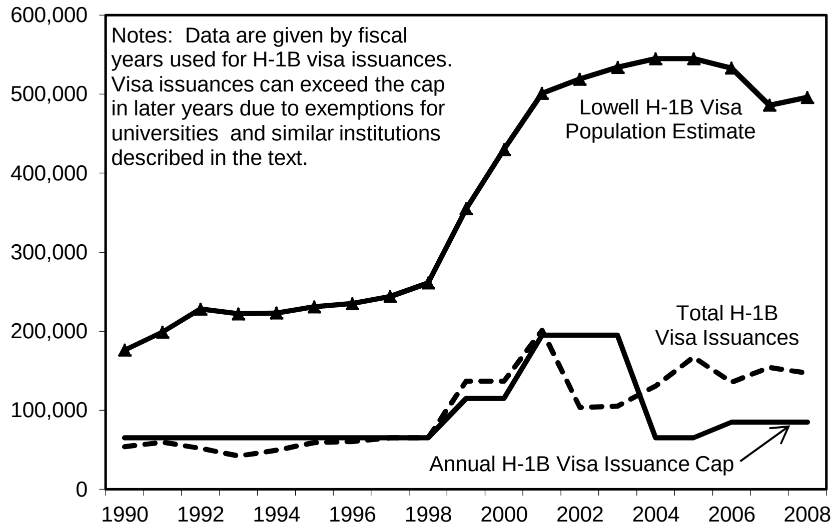


Figure 2.4: H-1B Visas and Population Estimates



CHAPTER III

Entry Costs and Increasing Trade

3.1 Introduction

A common feature of the rise in aggregate exports from several countries across the world is a significant expansion in the number of firms that export. A natural explanation that has been suggested by prior authors (e.g., Melitz 2003) is that the up-front costs of entering foreign markets have declined.[1] We test this idea for the first time using plant level data from the United States Census Bureau. We find that the US also saw significant foreign market entry over the period, with the fraction of plants that export rising from 21% in 1987 to 39% in 2006.[2] Across a number of different estimation approaches, however, we find little evidence for the idea that declines in the costs of entering foreign markets played a significant role in driving these trends. We instead argue that changes in other factors that govern export status were of a sufficient magnitude to explain the level of foreign market entry that we see in the data, without the need to appeal to falling entry costs.

Our analysis begins by presenting a number of descriptive statistics that provide new insight into the US experience. We find that the rise in the fraction of plants selling abroad mentioned above was broad-based; it was experienced across a wide

[1] See also Roberts and Tybout (1997a).

[2] We discuss our data and how these and other figures are calculated in Section 3.2.

range of industries as well as geographic regions. These extensive margin adjustments were matched with strong intensive margin adjustments, with average foreign sales per exporter also increasing substantially. Over time, changes along both of these margins had a large influence on aggregate trade volumes. Finally, at the same time that more plants began to sell abroad, the level of persistence in export market status remained quite stable over time.

We next turn to understanding how much of a role declines in the costs of entering foreign markets played in these trends. As these costs cannot be directly observed with current data sources, we need to use models of firm behavior to estimate their magnitude. Thus, to get a comprehensive perspective we consider both reduced form and structural estimation approaches. Our reduced form analyses provide a tractable way of addressing this question for the US manufacturing sector as a whole and allow for a wide variety of robustness checks. This approach, however, does not allow us to directly estimate the magnitude of changes in these costs. In our estimations, coefficient parameters in the regression specification are directly related to the costs of entering foreign markets. We let these coefficients differ across the earlier and later parts of the sample to look at how the costs compare. Our estimates imply similar magnitudes for these parameters across the two different periods. These findings suggest small changes in the barriers to entry in foreign markets.

We then turn to a set of structural estimations that use the methodology developed by Das, Roberts, and Tybout (2007). This approach allows us to estimate the average level of foreign market entry costs that plants face in a given period. The methodology is attractive in that it provides numerical estimates of how these costs have changed and is flexible in accounting for other factors that determine exporting behavior. Estimations require the use of computationally intensive Bayesian Monte

Carlo Markov Chain methods, however. We are thus constrained to focusing our analysis on understanding the experiences of a small set of industries. We estimate these costs across 1987-1997 and 1992-2003 and compare the results for these two time periods. Three of the four industries that we consider experienced roughly similar or rising costs across the two different panels and the fourth saw a moderate decline. Taken together, the results from the reduced form and structural estimations are evidence that declines in the costs of entering foreign markets have been modest at best. The level of responsiveness of export market participation to changes in the costs of entering foreign markets predicted by recent models of international trade suggests that these changes are unlikely to have played a large role in the changes that we see in the data.

We conclude with an analysis of whether changes in other factors that determine export status were of a sufficient magnitude to explain these trends. Specifically, we investigate whether a calibrated model of plant heterogeneity and international trade akin to that of Chaney (2008) can match the extensive margin adjustments that we see in the data. Keeping other factors such as the costs of entering foreign markets as well as trade-related variable costs stable, we find that growth in foreign income is sufficient to explain the rise in the fraction of exporters. Our accounting exercise demonstrates that a reduction in the costs of entering foreign markets is not needed to account for these trends in a standard model. These calculations lend credibility to our estimation results and point to a significant role for foreign economic growth in explaining the rise of trade.

Our work addresses an issue that is relevant for a number of other countries in addition to the US. Several other studies have suggested that large-scale foreign market entry was experienced worldwide during this period. Indeed, of the studies that have used plant or firm level data to study the rise in exports from other nations, many have found that entry into foreign markets played a significant role in the expansion of trade. This work includes studies on the experiences of Chile, Colombia, Mexico, and Morocco.[3] Although there is little plant-level evidence on this question outside of these countries, we also see dramatic increases in the number of goods sold across countries in disaggregated industry-level trade data. These results are consistent with substantial foreign market entry by firms in different sectors for a wide range of countries. Papers documenting these trends include Evenett and Venables (2002), Broda and Weinstein (2006), and Harris, Kónya, and Mátyás (2011). Particularly notable is an acceleration in the growth of varieties traded during our sample period of 1987-2006. Taken together, these studies suggest that our estimations address a question of first-order importance for understanding the recent growth of worldwide trade.

Our analysis also fills a significant gap in the international trade literature. A large number of studies have looked at the effect of changes in variable trade costs on export and import patterns. While there has been some work on other factors such as transportation costs, this work has primarily focused on understanding the effects of changes in tariffs. Yet these costs are only one, albeit important, piece of the puzzle. Changes in the barriers to entry in foreign markets also can have significant effects on trade patterns. One reason why these changes have not yet been studied is that methods to estimate their magnitude have only been developed relatively recently. Another is that the data requirements for looking at how they

[3] These papers include Bergoeing, Micco, and Repetto (2011), Roberts, Sullivan, and Tybout (1995), and Clerides, Lach and Tybout (1996). Roberts and Tybout (1997a) provide a survey of several of these papers. A notable exception here is China; see Amiti and Freund (2010). In the US context, Bernard and Jensen (2004a) have also previously documented a significant increase in the fraction of manufacturing plants that export over the period 1987-1992. Bernard, Jensen, and Schott (2009) additionally report significant extensive margin entry for US firms in goods (agriculture, manufacturing, and mining) sectors across the two years 1993 and 2000.

have changed are quite high. Our work represents an initial effort to address this issue.

In the next section, we discuss our data sources and document several new stylized facts about US plants' exporting behavior from 1987 to 2006. Section 3.3 uses a model of export behavior to motivate reduced form estimations on the evolving nature of these costs. In Section 3.4 we describe the structural model that we use to estimate changes in these costs and the results that we get from our estimations. Section 3.5 performs an accounting exercise that looks at the contribution of other factors to the rise in export market participation such as increases in foreign income. Section 3.6 concludes.

3.2 Data and Stylized Facts

We use data from a number of different sources. Our data on aggregate industry exports come from two sources (i) the United Nations' Commodity Trade Statistics Database (Comtrade) and (ii) data from the US Census Bureau that was concorded to the 1987 US SIC classification system using the approach described in Pierce and Schott (2008). Information on price deflators is obtained from the NBER manufacturing productivity database (Bartelsman and Gray, 1996). The primary microdata for our analyses come from the Annual Survey of Manufactures (ASM) and Census of Manufactures (CMF) from the US Census Bureau. Both data sets contain information on the operations of US manufacturing plants. The CMF is conducted every year ending in 2 or 7 (e.g. 1987, 1992, etc.) and contains data on the universe of manufacturing establishments. The ASM is a survey of plants that is conducted in each intervening year. The sampling frames for these surveys are chosen two years after the most recent CMF.[4] These establishments are then followed over time for five years until the next ASM sampling frame is implemented. Given the inability to aggregate to the firm level in the ASM, we treat the plant as the unit of analysis. This is consistent with the literature that has used this data as well as a number of other trade-related studies on other countries. Wherever possible, however, we perform robustness checks on our analysis at the level of the firm, finding similar results. We begin our analyses in 1987, the first year that comprehensive data on export revenues were collected.

The sample designs of these data sets impose some structure on our analysis. The ASM includes large plants with certainty but samples smaller plants according to their contribution to output. Due to the loss of non-certainty cases across different ASM panels, we limit our sample for panel analyses to plants with 250 or more employees. This avoids a number of challenges involved in following smaller plants over time and allows for comparability with previous studies that have used a similar approach. Despite this restriction, however, our data covers a significant portion of economic activity and the great majority of export volume.[5] Arkolakis (2010) has also suggested that export market entry behavior might be different for small firms, making the assumptions undergirding our analyses more appropriate for large producers.

With these data we develop a number of new stylized facts regarding the pace and character of trade growth since 1987. Figure 3.1 plots the percentage of plants with 20 or more employees that export in each year from 1987 to 2003.[6] The overall

[4]Over the period 1987-1998 plants with more than 250 employees were sampled with certainty in the ASM. In the 1999-2003 ASM this threshold was increased to 500 employees and was further raised to 1000 in the 2004-2008 ASM. As the sampling probability is inversely related to a plant's contribution to output, plants between 250 and 500 employees are still sampled with a high degree of certainty in 1999-2003, however. In our estimations that span these years, we reweight the plants accordingly.

[5]Bernard and Jensen (2004a) use a similar sample and note that it accounts for 41% of employment, 52% of shipments, and 70% of exports in 1987.

[6]Similar to several other studies, we focus on plants with 20 or more employees. In all of our analyses we drop

upward trend is unmistakable; 21% of plants exported in 1987 and 35% exported in 2003. Although we focus our analysis on the 1987-2003 period, this percentage rises steadily after 2003 to 39% in 2006. A number of different aspects of these trends are of note. First, we can get a sense of how much of these trends were due to adjustments in exporting status by existing establishments. Amongst plants that had 20 or more employees in both the 1987 and 2002 Census of Manufactures, 29% export in 1987 and 39% export in 2002. These figures suggest that a large part of these trends were due to adjustments by plants that were in operation in 1987 but only sold domestically. Secondly, taking the 21% participation rate from 1987 as a baseline, new plants that entered the sample and remained in business until 2002 were somewhat more apt to sell abroad. Those that exited were only slightly less likely to be exporters. The difference between these two figures consequently added to the overall trend but was not the sole determining factor. These trends and foreign market entry by existing plants both contributed. Finally, the rise in the fraction of plants that exported over the period 1987-2003 was due to a 34% increase in the raw number of exporting plants and a 20% decline in the total number of plants. Since exiting plants included a large number of exporters, these declines in the total number of plants would have lowered the number of exporters if there had not been substantial foreign market entry.

Figures 3.2 and 3.3 look at the sectoral and geographic dimensions of the rise in export market participation. Figure 3.2 plots the percentage of plants that export in each industry in 1987 and 2003. While some industries saw larger changes than others, there has been a significant expansion in foreign market participation across nearly all sectors of the economy. Figure 3.3 demonstrates that the results in Figure

administrative records, which are essentially imputed data for small employers and new businesses. Due to disclosure concerns, estimates for 1987 and 1992 are from Bernard and Jensen (2004b).

3.1 were experienced broadly across different regions of the US. These results hold generally across states as well. We find similar results for Figures 3.1-3.3 if we instead limit the analysis to plants with 10 or more employees or 250 or more employees. In Tables 3.1 and 3.2 we document the time path of these sectoral and geographic trends across 5-6 year intervals, mostly using the CMF. While we find similar patterns to the overall trend by region, there is more heterogeneity in the timing and magnitude of foreign market entry across industries. The fact that the expansion in the fraction of plants that export has been pervasive across these two dimensions suggests that these trends were not driven by idiosyncratic factors such as the rise of high-tech industries.

In a similar vein, we also looked at how the composition of the destinations of aggregate exports changed over time. We find that although export volumes rose sharply over the period, with a few exceptions trade shares have remained quite stable. For example, Germany accounted for 5.4% of total US exports in 1987 and accounted for 5.8% in 2003. Among the top 40 export destinations in 1987, the rank correlation between export shares in 1987 and 2003 is 88%. These countries account for 92% of total US exports in 1987. We present the shares for the top 20 export destinations in 1987 and their corresponding shares in 2003 in Table 3.4.

Although we focus on the determinants of changes in export status, it is clear that there have also been significant expansions in total exports through the intensive margin of trade. These changes suggest that the incentives to sell abroad have increased significantly over time. In the aggregate, manufacturing exports as a percentage of GDP rose by 35% over the period 1987-2003. In Figure 3.4 we graph the average level of real foreign sales across exporting plants by year. Estimates are for plants with 20 or more employees and exclude the computer and semiconductor industries due to the strong decline in prices over time; estimates including all industries show a significantly stronger increase over time. In order to look at percentage changes we normalize these figures such that the average in 1987 is set equal to one. We find that average foreign sales increased steadily by 49% over the time period. These results are robust to limiting the sample to plants with 10 or more employees, 250 or more employees, or to single plant firms. They also hold when looking at firms in different Census of Manufactures samples. Thus, even though both the number and fraction of plants that export increased significantly, the average level of foreign sales for each of these plants has also increased. Eaton, Kortum and Kramarz (2011) suggest that decreases in the costs of entering foreign markets should lower average foreign sales; these figures thus suggest that either these costs have increased or that other factors were important in determining export trends.

To get a sense of how changes in the extensive margin have affected overall trade volumes, we use information from each year in which we have data from the Census of Manufactures. This allows us to track the universe of small as well as large plants over time. The fact that the intensive margin dominates trade volumes in the short-run has been documented by, among others, di Giovanni and Levchenko (2009) and Bernard, Jensen, Redding, and Schott (2007). Authors have only recently begun to focus on the relative importance of the extensive margin for aggregate trade volumes over longer time horizons, however. Table 3.5 reports the contribution to Census year aggregate exports by plants that exported in a given prior Census year. When the time horizon is greater than five years we limit these figures to plants that exported in each intervening Census year. Thus, only 46% of aggregate exports in 2002 came from plants that exported in 1987, 1992, and 1997. These numbers underestimate the importance of changes along the extensive margin since they are not restricted to plants that exported continuously in all prior years.[7] Removing any continuous exporting restriction, we find that 57% of trade in 2002 is from plants that export in 1987 and 2002.

In Figure 3.5 we look at annual rates of entry, exit, and export status persistence. Plants that persist are those which continue exporting or only selling to the domestic market. In each year we limit the sample to plants that existed in the previous year, such that the percent of plants that enter, exit, and keep the same export market status adds up to 100% in each year. Due to changes in the plants included across different ASM sampling frames, we limit the graph to plants with 250 or more employees. We find similar trends, however, within and across different ASM sampling frames for plants with 20 or more employees. In order to make the changes in the series clear we use two different axes, with entry and exit rates depicted using the scale on the right axis and persistence levels on the left axis.

It is our expectation that if the barriers to entry in foreign markets fell dramatically, we should see significantly less persistence in export market status over time. Indeed, if they fell to zero, plants would be able to enter without cost. They would also be more likely to exit since re-entry would also be free. This intuition is developed more formally in Sections 3.3 and 3.4. We instead find that the level of persistence stayed roughly constant over time, with a mean of 85% and a standard deviation of less than 3%. The level of persistence amongst exporters, which can be denoted as $E\left[y_{it} \mid y_{it-1} = 1\right]$ where y_{it} is a 0/1 indicator for export status, also remained stable over time. Thus, export market participation increased at the same time that export status persistence remained stable. The rise in the number of ex-

[7] We are unable to calculate year-to-year statistics based on continuously exporting plants due to the breaks between ASM panels. These figures echo related results reported in Bergoeing, Micco, and Repetto (2011) for Chile 1990-2007, Bernard, Jensen, Redding and Schott (2007) for the aggregate US economy (including non-manufacturing sectors) for 1993-2003, and Eaton, Eslava, Kugler and Tybout (2007) for Colombia 1996-2005. The analysis in Table 3.5 is done with the plant identifier lbdnum. The results from using the alternative plant identifier ppn are similar.

porters documented in Figures 3.1-3.3 was driven by entry rates regularly outpacing exit rates, rather than changes in the frequency of entry and exit. These results suggest that dramatic declines in the costs of entering foreign markets are unlikely.

3.3 Reduced Form Estimations

In this section we consider reduced form evidence on how the costs of entering foreign markets have changed over time. While our structural estimations in the next section will allow us to study a number of different industries in depth, the reduced form approach will give us a sense of how these costs have changed for the manufacturing sector as a whole. Drawing upon the seminal work of Dixit (1989) and Baldwin and Krugman (1989), several prior studies have used a simple binary choice model of whether or not to export to test for the existence of barriers to entry in foreign markets.[8] Here, we use this approach to get a sense of how these costs have changed over time. The basic premise of the model is that a plant will sell abroad if the benefits from exporting exceed the additional costs of doing so. The benefits include the extra gross revenues that it could make as well as any option value associated with being an exporter in the future. In addition to the extra expenses associated with increased production, the costs include barriers to entry for plants that did not export previously. Specifically, a plant that has not exported for more than two years must pay a sunk cost F_0 to enter the foreign market and a re-entry cost F_R if it last exported two years ago.[9] The model can be reduced to a simple decision rule where

[8]See Roberts and Tybout (1997b), Bernard and Wagner (2001), and Bernard and Jensen (2004a).

[9]Prior studies have found little difference between the costs of entering foreign markets anew and entering after three years of not exporting. They have also found a small difference between F_0 and F_R above. The model can be extended to include a cost of exiting L, which makes the coefficient α_1 in equation (3.2) a function of $F_0 + L$. We think these costs are likely to be small. See Heckman (1981a) and Chamberlain (1985) for discussions of econometric issues relating to identifying true state dependence.

$$y_{it} = \begin{cases} 1 & \text{if } p^*_{it} - F_0 + F_0 \cdot y_{it-1} + (F_0 - F_R) \cdot \tilde{y}_{it-2} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{3.1}$$

Here y_{it} is plant $i's$ export status in year t and $\tilde{y}_{it-2} = y_{it-2}(1 - y_{it-1})$ is an indicator function for whether the plant last exported two years prior to year t. The term p^*_{it} can be written as

$$p^*_{it} = p_{it} + \delta \left(E_t \left[V_{it+1} \mid y_{it} = 1 \right] - E_t \left[V_{it+1} \mid y_{it} = 0 \right] \right)$$

It is determined by the extra gross profit that the plant could make by exporting this year p_{it} plus the option value associated with being an exporter next period. This option value, in turn, is given by the difference in the discounted future expected value of being an exporter today relative to only selling domestically. In the model if there are no costs to entering the foreign market, the condition for exporting in equation (3.1) collapses to $p_{it} \geq 0$. In this case, the plant decides whether or not to export based solely on what is most profitable today and ignores dynamic considerations. Thus, once controlling for factors that account for changes in p_{it}, if there are no costs to entering foreign markets we should see a lack of state dependence in exporting status.

To obtain an estimating equation that will allow us to look at changes in F_0 and F_R we need to parameterize $p^*_{it} - F_0$. A number of factors likely influence this term, such as changes in plant productivity and fluctuations in foreign income. We use the following functional form

$$p^*_{it} - F_0 \approx \mu_i + X'_{it}\beta + \phi_t + \varepsilon_{it}$$

to develop the specification

$$y_{it} = \mu_i + X'_{it}\beta + \alpha_1 \cdot y_{it-1} + \alpha_2 \cdot \tilde{y}_{it-2} + \phi_t + \varepsilon_{it} \tag{3.2}$$

This equation provides the basis for our estimations. The vector X_{it} contains a number of covariates that predict export market participation. These include the ratio of nonproduction to total employment, an indicator function for change of product and the logarithms of employment, total factor productivity, and average wages. Productivity is estimated with the approach of Levinsohn and Petrin (2003). We also include an industry-level trade-weighted exchange rate series.[10] Unobserved plant specific factors that influence p^*_{it} are captured in the term μ_i. Business cycle effects and other time varying factors are absorbed into the year fixed effects ϕ_t. The coefficients $\alpha_1 = F_0$ and $\alpha_2 = (F_0 - F_R)$ parameterize the importance of barriers to entry in foreign markets. Larger estimates of α_1, for example, suggest higher sunk costs F_0.

Table 3.6 presents the results from estimating the specification in (3.2) over the period 1989-2003. Standard errors in parentheses are clustered at the plant level and plant-specific characteristics in X_{it} are lagged by one period in order to avoid issues of simultaneity. In column (1) we present our findings from estimating equation (3.2) as presented above. The coefficients on y_{it-1} and $\tilde{y}_{it-2}$ are quite similar to the magnitudes found in other studies for the US that consider different time periods.[11] Column (2) presents our baseline results. We include interaction terms of the variables y_{it-1} and $\tilde{y}_{it-2}$ with an indicator function for the post-1995 period $Post_t$. The coefficient estimates on these interaction terms will then indicate how the costs F_0 and F_R compare in the second half of the period to those in the first. We find a

[10] Each exchange rate is a geometric export-weighted average of bilateral real exchange rates where the weights are constructed using 3 digit SIC export data. We follow the aggregation method used by the US Federal Reserve, as detailed in Loretan (2005). We use the same industry-level exchange rate series for both our reduced form estimations and structural analysis.

[11] See Bernard and Jensen (1999), Bernard and Jensen (2004b).

small decline in the coefficient α_1 in the second part of the panel and a somewhat larger decrease in α_2. Controlling for other factors, exporting last year raises a plant's probability of exporting by 44% over the period 1989-1995 and by 40% over 1996-2003. These results are consistent with those found in column (1) in terms of how the coefficients on the interaction terms compare to those on the unaltered lagged export status covariates. Given the magnitudes of the coefficients on the interaction terms, we interpret these estimates to suggest relatively small declines in the costs F_0 and an increase in the costs of re-entering foreign markets F_R. The size of each of these coefficients, however, suggests that the changes in these costs are unlikely to have been significant enough to have played a determinative role in export trends.

In our estimations in columns $(1)-(2)$ we allow entry into the sample but drop plants that died during the sample period. This approach allows us to abstract from plant death, which is not explicitly a part of the model. We present the results from alternatively considering a fully balanced panel with no entry or exit into the sample over the 1989-2003 period in column (3) . We find similar estimates to those shown in columns (1) and (2). This is reassuring not only for the validity of our reduced form approach but also for our structural estimations, where we are constrained to use a balanced panel approach. We also considered a sample that contained no restrictions in terms of entry and exit into the sample. We find similar results with this sample definition as well.

In column (4) we estimate our baseline specification on a sample limited to plants in the industries that we consider for our structural analyses. These industries are the Preserved Fruits and Vegetables (SIC 203), Metal Forgings and Stampings (SIC 346), Aircraft and Parts (SIC 372), and Measuring and Controlling Devices (SIC

382) industries. We discuss how these sectors were chosen in Section 3.4. Due to concerns about disclosure, we pool the plants from different industries and consider a panel in which both entry and exit are allowed. We find similar results to the overall trend for these industries. Both the magnitudes and changes in the coefficients α_1 and α_2 are similar to those found in columns $(1)-(3)$. These results suggest that the industries that we consider for our structural analyses are representative of aggregate trends.

In addition to the results presented in Table 3.6, we come to similar conclusions when considering alternative approaches to our baseline specification. These include using different definitions of the post-period indicator function $Post$, only considering plants with 350 or more employees, dropping the computer and semiconductor industries, using different covariates in the term X_{it}, using current values of plant-specific characteristics in the vector X_{it}, adding the variable "Last exported three years ago" and its interaction with $Post_{95}$, and limiting the analysis to single-plant firms.[12] This last robustness check is especially reassuring as it alleviates concerns related to multi-plant firms. Standard errors are similar when clustering by firm or by industry at the 3 digit SIC level. The estimations using a balanced panel were also robust to these alternative estimation approaches.

3.4 Structural Estimation

3.4.1 Model

In this section, we turn to a structural approach to address how the costs of entering foreign markets have evolved. The extra structure afforded by the model

[12]Specifically we alternately considered defining the post period as the years after 1993, 1994, 1996 or 1997. We define the computer and semiconductor industries as the SIC87 sector codes 357 and 3674 over 1987-1997 and the NAICS sector code 334 over 1997-2003.

allows us to provide numerical estimates of the costs of entering foreign markets in different time periods. Specifically, we use the estimation methodology developed by Das, Roberts, and Tybout (2007) to look at the average level of foreign market entry costs facing plants over the 1987-1997 and 1992-2003 periods. Comparing these cost estimates across the two panels will then give us a sense of how they have changed. In addition to addressing the question of the determinants of the rise in export intensity, our results contribute to the emerging literature on estimating the magnitude of these barriers. Indeed, these costs have not been estimated with panel data outside of Colombia and Chile.

Here we lay out the basics of the model underlying the estimation approach; further details are contained in the appendix. All plants in the model serve the domestic market and face the choice of whether or not to sell their goods abroad. The foreign and domestic markets are segmented from one another and are both monopolistically competitive. We abstract from entry and exit into production in the domestic market, requiring the use of a balanced panel in our estimations. We assume that plants' marginal costs do not respond to output shocks, simplifying the model significantly by isolating the decision to serve foreign markets from domestic concerns. Plants are forward-looking in the sense that, although they do not know what their future realizations of marginal costs, foreign demand, and the exchange rate will be, they know the Markov processes by which these factors evolve and set their expectations accordingly.

The log potential profits from selling in the foreign market π_{it}^* for plant i in year t is defined as

$$\ln\left(\pi_{it}^*\right) = \psi_0 z_i + \psi_1 e_t + v_{it} \tag{3.3}$$

where z_i indexes time-invariant plant characteristics and e_t is the exchange rate facing the plant. v_{it} is a stationary, serially correlated disturbance term that captures shifts in factors that determine potential export profits. Examples of these factors include changes in productivity, factor input prices, tariffs, transportation costs, and demand. Although this general form is quite parsimonious, it allows for significant flexibility in accounting for many of the other potential explanations for changes in export status. We assume that v_{it} is the sum of m stationary and independent $AR(1)$ processes. Formally, we have $v_{it} = \sum_{j=1}^{m} x_{jit}$ where i indexes plants, t the time period, and j the type of potential shock. Each of these potential shocks can be written $x_{jit} = \lambda_x^j x_{jit} + w_{xjt}$, where w_{xjt} is normally distributed with mean zero and variance σ_{wj}^2. The composite term v_{it} therefore follows an $ARMA\,(m, m-1)$ process. We define x_{it} as the $m \times 1$ vector of shocks to profits, where $v_{it} = \iota' x_{it}$ and ι is a vector of ones. The exchange rate e_t follows the AR(1) process $e_t = \lambda_0 + \lambda_e e_{t-1} + w_{et}$ where w_{et} is normally distributed with mean zero and variance σ_w^2. The parameters λ_0, λ_e, σ_w and the distribution of w_{et} are known to all plants. For ease of exposition, we denote $\Psi = (\psi_{01}, ..., \psi_{0k}, \psi_1) = (\psi_0, \psi_1)$ and collect the parameters λ_x^j and σ_{wj} into the diagonal matrices Λ_x and $\sum_\omega$.

The relevant variable for the empirical analysis of a plant's decision of whether or not to export is the level of foreign profits that it could make. Our data, however, only contain information on total revenues and export revenues. In order to make estimation possible we draw upon two aspects of the model mentioned above: first, markets are monopolistically competitive, and second, foreign and domestic markets are segmented. We further denote c_{it} as the marginal cost of production, $\eta_i > 1$ as a plant-specific foreign demand elasticity, and P_{it}^f as the domestic currency price of exports. If the plant exports, it would optimally choose to price its goods such that $c_{it}^f = P_{it}^f \left(1 - \eta_i^{-1}\right)$. This implies that potential foreign revenues R_{it}^{f*} and variable costs C_{it}^{f*} to exporting can be written as $C_{it}^{f*} = R_{it}^{f*}\left(1 - \eta_i^{-1}\right)$ if we multiply both sides of this expression by the optimal quantity of exports. Using the fact that $\pi_{it}^{*} = R_{it}^{f*} - C_{it}^{f*}$, this condition implies that potential export profits are given by

$$\pi_{it}^{*} = \eta_i^{-1} R_{it}^{f^*} \tag{3.4}$$

Taking logs and substituting this expression into (3.3) yields

$$\ln\left(R_{it}^{f^*}\right) = \ln\left(\eta_i\right) + \psi_0 z_i + \psi_1 e_t + \upsilon_{it} \tag{3.5}$$

This relationship provides a way to estimate the parameters that determine export profits and allows us to account for a significant amount of plant heterogeneity in our estimations to follow. It does, however, create an incidental parameters problem with the introduction of the parameters $\eta = \{\eta_i\}_{i=1}^{n}$. As the number of plants in the sample grows, so too does the number of parameters.

To solve this problem we explicitly use data on costs and revenues. This information can be used to identify η. We begin by assuming that the ratio of foreign demand elasticities to domestic demand elasticities is $1+\upsilon$ for all plants in the industry. By steps analogous to those above, profit maximization and segmented markets imply that we should observe $C_{it}^{d} = R_{it}^{d}\left(1 - \eta_i^{-1}[1+\upsilon]\right)$ in the domestic market. Invoking the assumption of segmented markets, optimally selected production for all markets must satisfy

$$C_{it} = C_{it}^{f} + C_{it}^{d} = R_{it}^{f}\left(1 - \eta_i^{-1}\right) + R_{it}^{d}\left(1 - \eta_i^{-1}\left(1+\upsilon\right)\right) \tag{3.6}$$

Dividing this expression by $R_{it} = R_{it}^{f} + R_{it}^{d}$, rearranging, replacing optimal with realized values, and including an error term ξ_{it} yields

$$1 - \frac{C_{it}}{R_{it}} = \eta_i^{-1}\left(1 + \upsilon\frac{R_{it}^{d}}{R_{it}}\right) + \xi_{it} \tag{3.7}$$

Here R_{it}^{d}, R_{it}, and C_{it} are the plant's realized domestic revenue, total revenue, and total variable cost. We assume that the error term ξ_{it} comes from measurement error in the costs C_{it} and follows the AR(1) process $\xi_{it} = \lambda_{\xi}\xi_{it-1} + w_{\varsigma t}$, where $w_{\varsigma t}$ is normally distributed with variance σ_{ς}^{2}. We can then use this expression to form the density $f_c\left(C_{i0}^{T} \mid R_{i0}^{fT}, R_{i0}^{dT}, \theta\right)$.

Equation (3.3) gives us an expression for the baseline level of profits that plants earn from foreign markets in each period. In looking at the plant's dynamic problem of whether or not to export, we further allow each plant to receive a shock to profits each period of $\kappa + \varepsilon_{1it}$. κ is common to all plants and ε_{1it} is allowed to vary across plants i and years t. Plants must also pay an up-front, sunk cost to enter foreign markets $\gamma_s z_i + \varepsilon_{2it} - \varepsilon_{1it}$. These one-time costs γ_s depend on time invariant plant characteristics z_i, are paid fully in the first year of exporting, and are allowed to vary across plants and time. Examples of these costs include market research, setting up distribution channels, learning about foreign regulations and documentation requirements, and a number of other non-tariff barriers. It is the estimation of these parameters γ_s in which we are most interested. Note that γ_s parameterizes the typical costs that plants face and not necessarily the costs that are paid by plants that begin to sell abroad. Indeed, all else equal, the plants that enter are those that are likely to have drawn a favorable shock of $\varepsilon_{2it} - \varepsilon_{1it}$. We assume that ε_{jit} are serially uncorrelated, normally distributed with mean zero and variance $\sigma_{\varepsilon j}^{2}$, and are uncorrelated with v_{it} and e_t for each $j = 1, 2$. For the sake of exposition, we let $\sum_{\varepsilon} = diag\left(\varepsilon_{1it}, \varepsilon_{2it}\right)$ and $\Gamma = (\gamma_{s1}, \gamma_{s2}, ..., \gamma_{sk}, \kappa) = (\gamma_s, \kappa)$.

We are now in a position to describe the plant's decision of whether or not to export. Let y_{it} be an indicator variable for whether plant i exported in year t. Using the expression for gross potential export profits π_{it}^* from (3.3), we can write

$$u(\cdot) = \begin{cases} \pi_{it}^*(e_t, x_{it}, z_i) + \kappa + \varepsilon_{1it} & \text{if } y_{it} = 1 \text{ and } y_{it-1} = 1 \\ \pi_{it}^*(e_t, x_{it}, z_i) + \kappa - \gamma_s z_i + \varepsilon_{2it} & \text{if } y_{it} = 1 \text{ and } y_{it-1} = 0 \\ 0 & \text{if } y_{it} = 0 \end{cases} \tag{3.8}$$

The plant's potential net export profits depend on its prior export status, since we assume that sunk costs have to be paid if the plant did not export in the previous year.

In each period t, the plant observes the values of e_t, x_{it}, ε_{jit}, and z_i and forms its expectations about the future using the fact that it knows the processes by which these terms evolve. The plant then determines the decision rule of whether or not to export $y_{it} = y(e_t, x_{it}, z_i, \varepsilon_{jit}, y_{it-1} \mid \theta)$ which maximizes its net discounted expected profit stream over a 30 year horizon. Formally, we have the Bellman equation

$$V_{it} = \max_{y_{it} \in \{0,1\}} \{u(e_t, x_{it}, z_i, \varepsilon_{jit}, y_{it-1}, y_{it} \mid \theta) + \delta E_t V_{it+1}\} \tag{3.9}$$

where

$$E_t V_{it+1} = \int_{e'} \int_{x'} \int_{\varepsilon'} V_{it+1} \cdot f_e(e' \mid e_t, \theta) \cdot f_x(x' \mid x_t, \theta) \cdot f_\varepsilon(\varepsilon' \mid \varepsilon_t, \theta)\, d\varepsilon' dx' de'$$

and θ collects all the parameters

$$\theta = (\Psi, \eta, \upsilon, \Lambda_x, \Sigma_\omega, \Gamma, \Sigma_\varepsilon, \lambda_0, \lambda_e, \sigma_w, \lambda_\xi, \sigma_\varsigma)$$

The decision rule of whether or not to export can be written as a binary choice problem $y_{it} = I(y_{it}^* > 0)$. Here $I(\cdot)$ is an indicator function and y_{it}^* is a comparison of the benefits from exporting and from not exporting

$$y_{it}^* = u(e_t, x_{it}, z_i, \varepsilon_{it}, 1, y_{it-1} \mid \theta) + \delta \Delta E_t V_{it+1}(e_t, x_{it}, z_i \mid \theta) \tag{3.10}$$

where

$$\Delta E_t V_{it+1}\left(e_t, x_{it}, z_i \mid \theta\right) = E_t\left[V_{it+1} \mid y_{it}=1\right] - E_t\left[V_{it+1} \mid y_{it}=0\right]$$

The first term in (3.10) reflects the direct benefits today from exporting, whereas the second term reflects the option value of being an exporter tomorrow.

3.4.2 Estimation

Using the expressions developed above to describe a plant's intensive and extensive margin exporting decisions, we then develop a likelihood function that allows us to estimate the parameters in one step

$$L\left(D \mid \theta\right) = \prod\nolimits_{i=1}^{n} f_c\left(C_{i0}^{T} \mid R_{i0}^{fT}, R_{i0}^{dT}, \theta\right) \cdot P\left(y_{i0}^{T}, R_{i0}^{fT} \mid e_0^{T}, z_i, \theta\right) \tag{3.11}$$

Here $D = \{D_i\}_{i=1}^{n}$ denotes the data for all firms. $f_c\left(C_{i0}^{T} \mid R_{i0}^{fT}, R_{i0}^{dT}, \theta\right)$ is determined by the expression in (3.7) and the likelihood $P\left(y_{i0}^{T}, R_{i0}^{fT} \mid e_0^{T}, z_i, \theta\right)$ is formed from the relationships implied by the extensive margin decision. We provide more details about the construction of $P\left(y_{i0}^{T}, R_{i0}^{fT} \mid e_0^{T}, z_i, \theta\right)$ in the appendix. Estimating the likelihood function $L\left(D \mid \theta\right)$ with classical methods presents two problems. First, while this feature of the approach allows us to account for a significant amount of plant heterogeneity, we are faced with an incidental parameters problem in that we need to estimate $\eta = \{\eta_i\}_{i=1}^{n}$. To add to this, the likelihood function is highly non-standard and unlikely to be globally concave in θ. To circumvent these issues, we use a Bayesian approach and write the posterior distribution of the parameters with $P\left(\theta \mid D\right) \propto q\left(\theta\right) L\left(D \mid \theta\right)$, where $q\left(\theta\right)$ gives our prior beliefs about the parameters. To characterize the posterior distribution $P\left(\theta \mid D\right)$, we then use the random walk Metropolis-Hastings algorithm. This algorithm essentially allows us to estimate $E(\theta \mid D)$ by performing Monte Carlo integration using a Markov chain.

Computational constraints place some restrictions on the level of heterogeneity for which these estimates can account. To characterize the time invariant plant characteristics that affect sunk costs and export profits, we let z_i equal an indicator function based on plant size. The threshold for z_i is set to be equal to the median level of sales in 1987, such that half of the plants are considered large in the first panel for each industry. We keep this threshold for the second panel, capturing changes in plant sales. The number of $AR(1)$ processes additively included in the profit function disturbance term is set to two $v_{it} = x_{1it} + x_{2it}$, intuitively reflecting separate cost and demand shock processes. We set the discount rate δ to 0.9. In order to ease computational costs, we do not estimate the parameters for the exchange rate process simultaneously with the rest of the model. Instead, we estimate them separately using export-weighted industry real exchange rates constructed with the same approach as those described in Section 3.3. We fit each of these series with an $AR(1)$ process from 1972 until the last year of each panel to give estimates of $\hat{\lambda}_0$, $\hat{\lambda}_e$, and $\hat{\sigma}_w$. These parameters are then treated as fixed for the purposes of the estimation of the model.

For the rest of our parameters, we have to specify a prior distribution. With a few exceptions, we make these distributions reasonably diffuse to let the data speak for itself. To impose non-negativity on the variance parameters, our priors are that they are distributed log normally with a mean of zero and a variance of 2. Our priors on the root of each AR(1) process are that they are distributed uniformly on $(-1, 1)$. This ensures that these processes are stationary. We also set a more restrictive prior for η_i due to the incidental parameters problem. Following the empirical literature, we set the prior such that $\ln(\eta_i - 1) \sim N(2, 1)$. This implies a mean and standard deviation for η_i of 12.2 and 16.0, respectively. It also ensures that $\eta_i > 1$, which is a necessary condition for the model. The prior for υ, the parameter that determines the ratio of foreign and domestic demand elasticities, is also assumed to be uniform on $[-5, 5]$. The priors for other parameters are given in Table 3.7.

Given these preliminaries, it is possible to provide intuition about the main sources of variation used to identify the sunk cost parameters. First note that for any type of plant the probability of exporting is an increasing function of the gross potential profit stream that it could earn in foreign markets. If there are no barriers to entry, the probability that a plant exports today should not depend on whether it exported yesterday. Plants with similar gross potential profit streams should have the same probability of exporting regardless of their exporting history. If there are significant up-front costs, however, plants that previously exported should have a higher probability of exporting since they do not need to pay to enter. The higher these costs are, the bigger the difference should be between plants that exported previously and those that did not. Thus, differences in the exporting frequencies of plants with similar gross potential export profit streams but different exporting histories in our data provide significant identifying variance for the sunk cost parameters.

3.4.3 Results

In choosing the industries that we focused on, we used several criteria to narrow down our choices (i) there were enough plants in each panel to allow for identification (ii) the industry was sufficiently export oriented (iii) it did not experience large, idiosyncratic shocks that would make our results unrepresentative (iv) like aggregate exports, the overall destination composition of industry exports was relatively stable and (v) the industries were in different 2 digit SIC sectors in order to get a broad view.[13] As mentioned above, these criteria led us to consider four 1987 SIC industries: Preserved Fruits and Vegetables (SIC 203), Metal Forgings and Stampings (SIC 346), Aircraft and Parts (SIC 372), and Measuring and Controlling Devices (SIC 382). Table 3.13 lists the 4 digit subindustries that comprise these 3 digit sectors. We use two panels, 1987-1997 and 1992-2003, and estimate the level of sunk costs γ_s in each period.

Tables 3.8-3.12 present the results. In Table 3.8 we present the estimates for our main sunk cost parameters by industry. Tables 3.9-3.12 present the full estimation results for each industry and time period. For each parameter we report the estimated mean and standard deviation, although median values give similar results. All figures are in 1987 dollars. For each panel we consider 50k draws from the posterior distribution to construct our estimates.[14] Despite generally using highly diffuse prior distributions, the posterior distributions for most of our parameters are fairly concentrated. This suggests that the estimates are primarily informed by the data itself rather than the values that we chose for our priors. We looked at the results from several different levels of thinning the chain. Here we alternately constructed our estimates by dropping every 2nd, 5th, 10th, 50th, or 100th draw. This standard robustness check for Monte Carlo Markov Chain (MCMC) methods is often used to diagnose a lack of convergence of the chain to the posterior distribution $P(\theta \mid D)$ or slow movement of the chain across the parameter space ("slow mixing"). These

[13]Due to data constraints, we are limited in considering a model with only two countries. This assumption has advantages as well as drawbacks. Hanson and Xiang (2011) develop an empirical test to understand the structure of these costs. They find evidence that they are global rather than bilateral in nature. This noted, we limit our structural analyses to industries where the destination of industry exports have remained stable over time by region. Considering a number of industries further alleviates concerns related to this modeling choice.

[14]Acceptance rates are kept within the range suggested by the literature and we use a burn-in period of at least 50k iterations. We looked at a number of diagnostic statistics to check for convergence. These tests are reviewed at length in Brooks and Roberts (1998). See the appendix for further details about the MCMC estimation methods.

different levels of thinning all give comparable results.

Consistent with the small changes that we see in the reduced form estimations, we generally find comparable results for γ_s across the two different time periods. The Aircraft and Parts and Measuring and Controlling Devices industries experienced little change in the costs that they faced while the Preserved Fruits and Vegetables sector experienced a decrease and the Metal Forgings and Stampings industry saw a rise in the costs. Internal calculations using the elasticity estimates for each plant suggest that the magnitude of the sunk costs are equal to a few years of the average level of exporting profits. Interestingly, we find similar estimates for γ_s for larger and smaller plants across each of the panels. These results suggest that differences in plant size do not alter the costs that plants face in our samples. Elasticity estimates are also consistent with the values suggested by the literature. In concert with our estimates from Section 3.3, we interpret these results to suggest that declines in these costs are unlikely to have been a major factor for the level of entry that we see in the data.

One interesting aspect of our results is that we find that the costs increased over time for the Metal Forgings and Stampings industry. There are a number of factors that may have acted to raise the costs for this industry as well as keep the barriers to entry for other industries higher than they otherwise would have been. In what little survey evidence we have on these costs, firms list market research and redesigning their products for foreign markets as two of the primary costs that they face in beginning to sell abroad.[15] With the increasing integration of the world economy, market research costs may have increased substantially due to the need to identify and study competition from a greatly expanded number of source countries.

[15] See the study conducted for the World Bank found in First Washington Associates (1991).

Secondly, while most types of nontariff barriers have decreased in the last 25 years, technical barriers to trade have increased significantly. These include product specification, testing, and information disclosure requirements. These changes are seen in the data on nontariff barriers as well as in the rising concerns of policy makers in recent years. It is also consistent with the idea of "regulatory protectionism" that has been the subject of significant prior research. Table 3.14 presents results from a United Nations Conference on Trade and Development (2005) report that argues that these barriers to trade have expanded significantly over time. Finally, as the use of antidumping measures have grown significantly, the costs of developing an optimal strategy for entering foreign markets may have increased due to the need to spend more on market research and legal fees.[16] While beyond the scope of this chapter, we consider the effects of these factors to be an open area for future research.

3.5 Discussion

In this section we perform back-of-the-envelope calculations to better understand the determinants of the increase in the percentage of plants that export. Our intent is to investigate whether a standard model can match this rise without appealing to changes in the costs of entering foreign markets. This exercise will give us a sense of whether or not our estimates are reasonable. We find that the model can easily account for the patterns that we see in the data using standard calibrations of the parameters. Here we provide one particular accounting, although other approaches are also sufficient to match the data. We consider a two-country version of the

[16]For evidence on changes in the technical barriers to trade, see UNCTAD (2005), Henson and Wilson (2005), Kirk (2011), US Department of Commerce (2004), Maskus, Wilson, and Otsuki (2000), and Beghin (2008). Baldwin (2000) and Sykes (1999) provide discussions of regulatory protectionism and Blonigen and Prusa (2008) and Finger, Ng, and Wangchuk (2001) document the rise in antidumping cases.

model of Chaney (2008) and assume as he does that the distribution of productivity is Pareto. The main facts that we want to match are that 21% of plants exported in 1987 and that 35% exported in 2003. In the model, we can write this as

$$P\left(\phi > \phi_x^{87} \mid \phi > \phi_p^{87}\right) = \left(\frac{\phi_p^{87}}{\phi_x^{87}}\right)^{\theta} = .21 \tag{3.12}$$

and

$$P\left(\phi > \phi_x^{03} \mid \phi > \phi_p^{03}\right) = \left(\frac{\phi_p^{03}}{\phi_x^{03}}\right)^{\theta} = .35 \tag{3.13}$$

Here ϕ_p is the minimum level of productivity ϕ needed to produce which we will assume is stable $\phi_p^{87} = \phi_p^{03}$. ϕ_x is the threshold level needed to access foreign markets profitably. If we divide the expression in (3.13) by that in (3.12) we have

$$\left(\frac{\phi_x^{87}}{\phi_x^{03}}\right)^{\theta} = \frac{.35}{.21} = 1.67 \tag{3.14}$$

We next attempt to decompose this increase in participation by turning to the factors that define the cutoff in the model. The productivity that results in zero net profits from exporting in the model is

$$\phi_x = \left(\frac{f_x}{Y_j}\right)^{1/(\sigma-1)} \frac{w_i \tau_{ij}}{P_j}$$

so the ratio of exports cutoffs in these two years is

$$\frac{\phi_x^{87}}{\phi_x^{03}} = \left(\frac{f_x^{87}}{f_x^{03}}\frac{Y_j^{03}}{Y_j^{87}}\right)^{\frac{1}{\sigma-1}} \frac{w_i^{87}}{w_i^{03}}\frac{P_j^{03}}{P_j^{87}}\frac{\tau_{ij}^{87}}{\tau_{ij}^{03}} \tag{3.15}$$

The parameter $\tau_{ij} > 1$ is the level of iceberg transportation costs, w_i is the home country wage, P_j is the foreign price index, f_x is the cost of entering the foreign market, and Y_j is the level of foreign income. From the ASM, we know that real wage growth in US manufacturing has been quite stagnant. Furthermore, US manufacturing competitiveness $\frac{w_i}{P_j}$ is also stable or declining over the period. As discussed by several authors, with the exception of NAFTA, tariffs on US goods also did not change significantly over the period; they were in general quite low and stayed that way. Hummels (2007) in turn notes modest reductions in the ad valorem air and ocean freight rates on US goods over 1987-2003. Using a gravity equation framework that accounts for other important factors besides tariffs and transportation costs, Jacks, Meissner, and Novy (2008) also find little change in τ_{ij} for the US 1987-2000. Debaere and Mostashari (2010) further look at imports into the US over 1989-1999 and argue that changes in τ_{ij} have played a minor role in explaining the large changes in the range of goods imported into the US. This was due to both the small estimated effects of variable trade costs on the extensive margin of trade as well as the small changes in US protection over the period.[17]

Motivated by this empirical evidence as well as our estimations above, we consider matching the extensive margin trends that we see in the data assuming that $\tau_{ij}^{03} = \tau_{ij}^{87}$ and $\left(w_i^{87}/P_j^{87}\right) \div \left(w_i^{03}/P_j^{03}\right)$ stayed constant. Our work above further allows us to reasonably assume that $f_x^{03} = f_x^{87}$. After all these assumptions, raising both sides of (3.15) to θ gives

$$\left(\frac{\phi_x^{87}}{\phi_x^{03}}\right)^{\theta} = \left(\frac{Y_j^{03}}{Y_j^{87}}\right)^{\frac{\theta}{\sigma-1}} \tag{3.16}$$

The exponent $\theta/(\sigma-1)$ has been carefully estimated to be near unity and we will use the value of 1.06 from Axtell (2001) but any choice greater than one will give the same result. Using trade shares from 1987 as weights, we calculate a rise in

[17] Others, however, have argued for a larger effect of changes in variable trade costs on exports. See Yi (2003), Bernard, Jensen, and Schott (2006), and Cuñat and Maffezzoli (2007). For evidence of changes in wages in US manufacturing, see the figures in the Annual Survey of Manufacturers-based US Census publication *Statistics for Industry Groups and Industries: 2005*.

real foreign income amongst 40 top US export destinations of 67%.[18] With these equalities and $\theta/(\sigma - 1) = 1.06$ plugging into equation (3.16) yields

$$\left(\frac{\phi_x^{87}}{\phi_x^{03}}\right)^{\theta} = 1.67^{1.06} = 1.72$$

This suggests that observed growth of foreign incomes are sufficient to explain all of the change in export market participation as expressed in (3.14). This significant role for foreign income is consistent with the pervasive nature of these trends for all industries and US regions. Furthermore, it is compatible with empirical evidence from Baier and Bergstrand (2001), Jacks, Meissner, and Novy (2011), and Whalley and Xin (2011) who study the factors that drove aggregate worldwide exports since the 1950s.[19] Alternative assumptions that increases in w_i/P_j were cancelled by the modest declines in τ_{ij} would give us similar results. Finally, participation could be expected to increase even more if the minimum productivity to produce increased $\phi_p^{03} > \phi_p^{87}$, iceberg costs decreased, US competitiveness deteriorated, or and this is our main point, if entry costs fell.

3.6 Conclusion

In this chapter we have documented a significant shift towards exporting for US plants over 1987-2006. In looking at why this occurred we considered a natural explanation that has been suggested as a primary cause for similar trends in other countries: declines in the up-front costs of entering foreign markets. Across different

[18] We include the top 42 US export destinations in 1987 with the exception of Taiwan and Kuwait due to missing data. We consider changes in real foreign income and the real level of entry costs f_x due to units cancelling in the expression in parentheses in equation (3.15).

[19] For example Whalley and Xin (2011) use a calibrated trade model and find a 76% role for income growth in the factors that drove world trade 1975-2004. Baier and Bergstrand (2001) and Jacks Meissner, and Novy (2011) instead consider estimations based on the gravity equation and find similar results. They study the periods 1958-1988 and 1950-2000, respectively. As each of these papers study bilateral trade flows, however, these results do not distinguish between the roles of domestic productivity growth and foreign income growth in driving exports from a given country.

approaches to understanding this issue, we show that reductions in these barriers were unlikely to have played a significant role in these trends. We instead find that other factors that determine export market participation are sufficient to explain these trends. Our work represents an initial attempt to understand how the costs to entering foreign markets have evolved over time.

We close with a discussion of a few areas of research that are likely to be fruitful for future work. Firstly, qualitative evidence on the determinants of export market entry costs would be tremendously valuable. Despite the evidence presented here and their ubiquity in trade models, there is surprisingly little direct survey evidence about these costs. Retrospective research in this area could help us better understand the results presented above. Secondly, much of the work on understanding the effects of free trade agreements focuses on how declines in tariffs affect aggregate trade volumes. Total trade tends to increase through extensive margin adjustments following these agreements, however, and the details of these accords often include provisions likely to reduce barriers to entry. Disentangling these effects would significantly improve our understanding of how different impediments affect trade and would likely yield more accurate analyses of potential policy changes. Finally, an improved understanding of the experiences of other countries would also provide further insight into the evolution of the barriers to entry in foreign markets. We attempted to obtain data to expand our analysis to countries beyond the US, but were unable to locate a data set with sufficient history and detail. Further analyses on the experiences of firms in other countries would add greatly to our understanding of trends in international trade.

3.7 Appendix

In this appendix we provide further details about our structural estimation approach. We begin by describing how we develop the extensive margin likelihood in sections 3.7.1 and 3.7.2. We then describe our approach to calculating the option value associated with exporting $\Delta E_t V_{it+1}(e_t, z_i, x_{it} \mid \theta)$. A description of our Bayesian MCMC estimation approach closes. The discussion of the model here and in the main text follows Das, Roberts, Tybout (2007); see this paper for further details about the model and estimation approach.

3.7.1 Extensive Margin Likelihood

For the purposes of estimation, we can connect the binary choice decision problem laid out in the body of the text to a likelihood function that uses our data from US plants. We begin by writing observed export profit shocks as

$$v_i^+ = \left\{ \ln\left(R_{it}^f\right) - \ln(\eta_i) - \psi_0 \cdot z_i - \psi_1 \cdot e_t \mid R_{it}^f > 0 \right\}$$

We can then write the export profit shock for plant i in each year t as a function of these observed shocks and a set of m *iid* standard normal random variates μ_i such that $x_{it} = x_{it}\left(v_i^+, \mu_i\right)$. For each plant, we can write

$$\begin{aligned} P\left(y_{i0}^T, R_{i0}^{fT} \mid e_0^T, z_i\right) &= P\left(y_{i0}^T, v_i^+ \mid e_0^T, z_i\right) \\ &= P\left(y_{i0}^T \mid e_0^T, z_i, v_i^+\right) \cdot h\left(v_i^+\right) \\ &= \left[\int_{\mu_i} P\left(y_{i0}^T \mid e_0^T, z_i, x_0^T\left(v_i^+, \mu_i\right)\right) \cdot g(\mu_i)\, d\mu_i\right] \cdot h\left(v_i^+\right) \end{aligned}$$

where the density functions for μ_i and v_i^+ are given by $g(\mu_i)$ and $h\left(v_i^+\right)$. We discuss how to construct $g(\mu_i)$, $h\left(v_i^+\right)$ and the term $\Delta E_t V_{it+1}(e_t, x_{it}, z_i \mid \theta)$ in the next sections of the appendix. The value of $P\left(y_{i0}^T \mid e_0^T, z_i, v_i^+\right)$ will be calculated using the distribution of $g\left(\mu_i\right)$ and Monte Carlo integration, drawing several μ_i from $g\left(\mu_i\right)$, plugging into $P\left(y_{i0}^T \mid e_0^T, z_i, x_0^T\left(v_i^+, \mu_i\right)\right)$, and averaging. This term can then be linked to our data by factoring out the initial conditions such that

$$P\left(y_{i0}^T \mid e_0^T, z_i, x_0^T\left(v_i^+, \mu_i\right)\right) =$$

$$P\left(y_{i1}^T \mid e_1^T, z_i, x_1^T\left(v_i^+, \mu_i\right), y_{i0}\right) \cdot P\left(y_{i0} \mid e_0, z_i, x_0\left(v_i^+, \mu_i\right)\right)$$

Given computational constraints, we use Heckman's (1981) solution to the initial conditions problem, and estimate $P\left(y_{i0} \mid e_0, z_i, x_0\left(v_i^+, \mu_i\right)\right)$ using

$$P\left(y_{i0} \mid e_0, z_i, x_0\left(v_i^+, \mu_i\right)\right) =$$

$$\left(\Phi\left(\alpha_0 + \alpha_1' z_i + \alpha_2' x_0\left(v_i^+, \mu_i\right)\right)\right)^{y_{i0}} \cdot$$
$$\left(1 - \Phi\left(\alpha_0 + \alpha_1' z_i + \alpha_2' x_0\left(v_i^+, \mu_i\right)\right)\right)^{1-y_{i0}}$$

Using backward induction along with Rust's (1997) random grid algorithm, we can calculate $\Delta E_t V_{it+1}\left(e_t, x_{it}, z_i \mid \theta\right)$ in each period. We then further use the export market participation rule in (8) to develop the likelihood function

$$P\left(y_{i1}^T \mid e_1^T, z_i, x_1^T\left(v_i^+, \mu_i\right), y_{i0}\right) =$$

$$\prod_{i=1}^{T}\left[E_{\varepsilon_{it}}\left(I\left(y_{it}^* > 0 \mid e_t, z_i, x_t\left(v_i^+, \mu_i\right), \varepsilon_{it}, y_{it-1}\right)\right)\right]^{y_{it}} \cdot$$
$$\left[E_{\varepsilon_{it}}\left(I\left(y_{it}^* \leq 0 \mid e_t, z_i, x_t\left(v_i^+, \mu_i\right), \varepsilon_{it}, y_{it-1}\right)\right)\right]^{1-y_{it}}$$

Differences across plants and time in terms of export market participation, costs, and foreign and domestic sales will then help pin down our parameters of interest. In particular, variation in export market participation by firms that would earn similar levels of profits in export markets but that are different in terms of their prior foreign market presence will be important in identifying sunk entry costs.

3.7.2 Density Functions for Foreign Market Profit Shocks

In this section we describe how we construct $h\left(v_i^+\right)$ and $x_0^T\left(v_i^+, \mu_i\right)$ mentioned in Section 3.7.1. These are elements that form part of $P\left(y_{i0}^T, R_{i0}^{fT} \mid e_0^T, z_i\right)$. We begin by deriving the density function for

$$
\begin{aligned}
v_i^+ &= \left\{\ln\left(R_{it}^f\right) - \ln\left(\eta_i\right) - \psi_0 \cdot z_i - \psi_1 \cdot e_t \mid R_{it}^f > 0\right\} \\
&= \left\{v_{it} \equiv \iota' x_{it} \mid R_{it}^f > 0\right\}
\end{aligned}
$$

For each plant we observe $q_i = \sum_{t=0}^{T} y_{it}$ values of v_i^+. We first assume that each x_{it} process is in long-run equilibrium such that $x_{it} \sim N\left(0, \Sigma_\omega\left(I - \Lambda_x^2\right)^{-1}\right)$. Thus, we have $h\left(v_i^+\right) = N\left(0, \Sigma_{vv}\right)$ where $E\left[v_{it}^2\right] = \iota'\left(x_{it}x_{it}'\right)\iota = \iota'\Sigma_\omega\left(I - \Lambda_x^2\right)^{-1}\iota$ and $E\left[v_{it}v_{it-k}\right] = \iota'\Lambda_x^{|k|}\Sigma_\omega\left(I - \Lambda_x^2\right)^{-1}\iota$ where $k \neq 0$.

The next key element in constructing $P\left(y_{i0}^T, R_{i0}^{fT} \mid e_0^T, z_i\right)$ is to develop the function $x_0^T\left(v_i^+, \mu_i\right)$. We first write x_{i0}^T as an $mT \times 1$ vector $x_{i0}^T = \left(x_{i0}', \ldots, x_{iT}'\right)'$. Given the $q_i \times 1$ vector v_i^+ we can write

$$
x_{i0}^T \mid v_i^+ \sim N\left(\Sigma_{xv}\Sigma_{vv}^{-1}v_i^+, \Sigma_{xx} - \Sigma_{xv}\Sigma_{vv}^{-1}\Sigma_{xv}'\right)
$$

Here $\Sigma_{xx} \equiv E\left(x_{i0}^T \cdot x_{i0}^{T\prime}\right)$ and $\Sigma_{xv} \equiv E\left(x_{i0}^T \cdot v_i^{+\prime}\right)$; the elements of these matrices are given by $E\left(x_{it} \cdot x_{it+s}'\right) = \Lambda_x^{|s|} \cdot \Sigma_\omega \cdot \left(I - \Lambda_x^2\right)^{-1}$ and $E\left(x_{it} \cdot v_{it+s}\right) = \Lambda_x^{|s|} \cdot \Sigma_\omega \cdot \left(I - \Lambda_x^2\right)^{-1}\iota$.

See Chow (1983) for further discussion.

We can then use these expressions to write

$$x_{i0}^T = x_{i0}^T\left(v_i^+, \mu_i\right) = \begin{cases} Av_i^+ + B\mu_i & \text{if } q_i > 0 \\ \\ B\mu_i & \text{if } q_i = 0 \end{cases}$$

Here $A = \Sigma_{xv}\Sigma_{vv}^{-1}$, $BB = \Sigma_{xx} - \Sigma_{xv}\Sigma_{vv}^{-1}\Sigma_{xv}'$, and μ_i is an $mT \times 1$ vector of *iid* standard normal random variables with density function $g(\mu_i) = \prod_{j=1}^{mT}\phi(\mu_{ij})$. We can use this expression to form $x_{it} = x_t\left(v_i^+, \mu_i\right)$ and $x_{is}^T = x_s^T\left(v_i^+, \mu_i\right)$ that are then a part of

$$P\left(y_{i0}^T \mid e_0^T, z_i, v_i^+\right) = \int_{\mu_i} P\left(y_{i0}^T \mid e_0^T, z_i, x_{i0}^T\left(v_i^+, \mu_i\right)\right) \cdot g(\mu_i) \cdot d\mu_i$$

Specifically, we can then use this functional form to simulate $P\left(y_{i0}^T \mid e_0^T, z_i, v_i^+\right)$. This is done by (i) drawing a set of S vectors μ_i from $g(\mu_i)$ (ii) using the values to calculate $x_{i0}^T\left(v_i^+, \mu_i\right)$ and (iii) averaging over the resulting values to calculate $P\left(y_{i0}^T \mid e_0^T, z_i, v_i^+\right)$.

3.7.3 Calculating the Option Value $\Delta E_t V_{it+1}(e_t, z_i, x_{it} \mid \theta)$

In obtaining an estimate of the latent value of exporting

$$y_{it}^* = \left[u\left(e_t, z_i, x_{it}, \varepsilon_{it}, y_{it} = 1, y_{it-1} \mid \theta\right) - 0\right] + \delta\Delta E_t V_{it+1}(e_t, z_i, x_{it} \mid \theta)$$

the term $u(e_t, z_i, x_{it}, \varepsilon_{it}, y_{it} = 1, y_{it-1} \mid \theta)$ can be calculated using the functional forms presented in the text. To obtain an estimate for $\Delta E_t V_{it+1}(e_t, z_i, x_{it} \mid \theta)$ we begin by using backward induction over a 30 year time horizon to first calculate

$$V_{it}^{O} = \delta E_t V_{it+1}\left(e_{t+1}, x_{it+1}, z_i \mid y_{it} = 0, \theta\right)$$

$$V_{it}^{E} = \pi\left(e_{t+1}, x_{it+1}, z_i, \theta\right) - \kappa - \gamma_s \cdot z_i + \delta E_t V_{it+1}\left(e_{t+1}, x_{it+1}, z_i \mid y_{it} = 1, \theta\right)$$

$$V_{it}^{S} = \pi\left(e_{t+1}, x_{it+1}, z_i, \theta\right) - \kappa + \delta E_t V_{it+1}\left(e_{t+1}, x_{it+1}, z_i \mid y_{it} = 1, \theta\right)$$

Here V_{it}^{O} is the expected value of only selling domestically in period t, V_{it}^{E} is the expected value from entering the foreign market, and V_{it}^{S} is the expected value of continuing to sell abroad. The algorithm begins in the last year in which $E_t V_{it+1} = 0$ and then calculates V_{it}^{O}, V_{it}^{E}, and V_{it}^{S} backwards successively until the current period is reached. We use Rust's (1997) random grid algorithm to integrate numerically over the state variables x and e. We calculate

$$\begin{aligned} E_t\left[V_{it+1} \mid y_{it} = 1\right] &= E_t \max\left(V_{it+1}^{O}, V_{it+1}^{S} + \varepsilon_{1it+1}\right) \\ &= \int_{x_{t+1}} \int_{e_{t+1}} \left[\begin{array}{c} \Phi\left(\frac{V_{it+1}^{S} - V_{it+1}^{O}}{\sigma_{\varepsilon 1}}\right) \times \\ \left[V_{it+1}^{S} + \sigma_{\varepsilon 1} \cdot \left[\frac{\phi\left(\frac{V_{it+1}^{S} - V_{it+1}^{O}}{\sigma_{\varepsilon 1}}\right)}{\Phi\left(\frac{V_{it+1}^{S} - V_{it+1}^{O}}{\sigma_{\varepsilon 1}}\right)} \right] \right] \\ + \Phi\left(\frac{V_{it+1}^{O} - V_{it+1}^{S}}{\sigma_{\varepsilon 1}}\right) \cdot V_{it+1}^{O} \end{array} \right] \\ &\quad \cdot f\left(x_{t+1} \mid x_t\right) \cdot f\left(e_{t+1} \mid e_t\right) \cdot dx_{t+1} \cdot de_{t+1} \end{aligned}$$

and

$$\begin{aligned} E_t\left[V_{it+1} \mid y_{it} = 0\right] &= E_t \left[\max\left(V_{it+1}^{O}, V_{it}^{E} + \varepsilon_{2it+1}\right)\right] \\ &= \int_{x_{t+1}} \int_{e_{t+1}} \left[\begin{array}{c} \Phi\left(\frac{V_{it}^{E} - V_{it+1}^{O}}{\sigma_{\varepsilon 2}}\right) \cdot \\ \left[V_{it}^{E} + \sigma_{\varepsilon 2} \cdot \left[\frac{\phi\left(\frac{V_{it}^{E} - V_{it+1}^{O}}{\sigma_{\varepsilon 2}}\right)}{\Phi\left(\frac{V_{it}^{E} - V_{it+1}^{O}}{\sigma_{\varepsilon 2}}\right)} \right] \right] \\ + \Phi\left(\frac{V_{it+1}^{O} - V_{it}^{E}}{\sigma_{\varepsilon 2}}\right) \cdot V_{0it+1} \end{array} \right] \\ &\quad \cdot f\left(x_{t+1} \mid x_t\right) \cdot f\left(e_{t+1} \mid e_t\right) \cdot dx_{t+1} \cdot de_{t+1} \end{aligned}$$

3.7.4 Monte Carlo Markov Chain Methods

We take $S = 50k$ draws of the posterior distribution $P(\theta \mid D)$ to construct our estimates using the random-walk Metropolis-Hastings algorithm. These draws are taken after an initial burn-in period that allows the chain to converge to the posterior distribution. The means and standard deviations are estimated with $\bar{\theta} = \frac{1}{S}\sum_{s=1}^{S}\theta^s$ and

$$\sqrt{\frac{1}{S}\sum_{s=1}^{S}\left(\theta^s - \bar{\theta}\right)\cdot\left(\theta^s - \bar{\theta}\right)'}$$

where θ^s is a given draw of the entire parameter vector from the posterior distribution. We use a Metropolis-Hastings algorithm in which we update the different components of the parameter vector separately in each iteration of the chain. We choose to partition θ with $\theta^s = (\theta_1^s, \theta_2^s, \ldots, \theta_8^s)$ where $\theta_1 = \Psi$, $\theta_2 = \Lambda_x$, $\theta_3 = \Sigma_\omega$, $\theta_4 = \Gamma$, $\theta_5 = \Sigma_\varepsilon$, $\theta_6 = \eta$, $\theta_7 = (\upsilon, \rho, \sigma_\xi)$, $\theta_8 = \varsigma$. Once starting values for the chain are chosen, for each iteration we perform the following steps. These steps are then repeated for each iteration.

1. Draw a potential new value for one of the subvectors θ_i based on the value from the previous iteration of the chain. This can be written as $\tilde{\theta}_i^* = \tilde{\theta}_i^s + \upsilon_i^s$ where $\tilde{\theta}_i^s$ is the value of the subvector from the previous iteration and υ_i^s is a mean-zero vector of shocks. The covariance matrix for υ_i^s, Σ_{υ_i}, is chosen before the estimations begin and is held fixed throughout.

2. Define $\tilde{\theta}_{-i}^s$ as the set of parameters in θ excluding those in $\tilde{\theta}_i^s$. Calculate the ratio

$$\alpha_i^s = min\left(\frac{P\left(\theta_i^* \mid \theta_{-i}^s, D\right)}{P\left(\theta_i^s \mid \theta_{-i}^s, D\right)}, 1\right)$$

and update the set of parameters θ_i with

$$(\theta_i^{s+1}, \theta_{-i}^s) = \begin{cases} \left(\theta_i^*, \theta_{-i}^s\right) & \text{with probability } \alpha_i^s \\ \left(\theta_i^s, \theta_{-i}^s\right) & \text{with probability } 1 - \alpha_i^s \end{cases}$$

3. Conduct the same process for each block of parameters θ_i. Once this is done $\forall\ i$, we take the resulting value of θ as our draw from the chain. This process is repeated for each draw of the chain.

3.8 Tables and Figures

Table 3.1: Export Participation by Industry

	Plants that Export (%)			
Industry	1987	1992	1997	2003
Food	15	23	25	27
Tobacco	45	51	47	
(Beverage & Tobacco)				28
Textile Mill Products	16	25	28	
(Textile Mills)				40
(Textile Product Mills)				30
Apparel	5	9	13	13
Wood products	12	18	16	16
Furniture	10	25	24	18
Paper	19	31	32	35
Printing & Publishing	5	10	11	14
Chemicals	40	49	49	55
Petroleum & Coal	22	30	30	31
Plastics & Rubber	26	36	39	40
Leather	19	28	35	38
Nonmetallic Minerals	14	21	20	17
Primary Metals	27	39	39	43
Fabricated Metals	21	31	32	30
Machinery	33	43	41	56
Electronic & Other Electric Equipment	37	46	47	
(Electrical Equipment, etc.)				54
Instruments	48	55	56	
(Computer & Electronic Products)				58
Transportation Equipment	29	40	41	49
Miscellaneous Manufacturing	20	34	36	37
Total	21	30	32	35

Notes: The table lists the percentage of plants that export in each industry using the Census of Manufacturers in 1987, 1992, and 1997 and the Annual Survey of Manufacturers in 2003. Due to concerns about disclosure, the results reported for 1987 and 1992 are from Bernard & Jensen (2004b). The classification system used is 1987 US SIC for 1987-1997 and 2002 NAICS for 2003. Similar to other reported figures, estimates are for plants with 20 or more employees. While somewhat heterogeneous in size and timepaths, these results overall suggest that the trends pictured in Figure 3.1 were pervasive across industries. See also Figure 3.2.

Table 3.2: Export Participation by Region

	Plants that Export (%)			
Region	1987	1992	1997	2003
New England	25	37	37	42
Middle Atlantic	19	29	30	34
East North Central	25	34	35	39
West North Central	23	32	33	37
South Atlantic	18	27	29	32
East South Central	18	27	27	30
West South Central	19	28	28	31
Mountain	18	26	27	32
Pacific	21	31	31	33
Total	21	30	32	35

Notes: The table lists the percentage of plants that export in each US Census geographical division using the Census of Manufacturers in 1987, 1992, and 1997 and the Annual Survey of Manufacturers in 2003. We report the states corresponding to these divisions in Table 3.3. Similar to other reported figures, estimates are for plants with 20 or more employees. These results suggest that the trend pictured in Figure 3.1 was experienced widely across regions of the US. Indeed, the time paths of participation rates of each region match the overall trends across these years. See also Figure 3.3 and Table 3.3.

Table 3.3: Census Division of the States

Census Division	State	Census Division	State
New England	Connecticut	East South Central	Alabama
	Maine		Kentucky
	Massachusetts		Mississippi
	New Hampshire		Tennessee
	Rhode Island		
	Vermont	West South Central	Arkansas
			Louisiana
Middle Atlantic	New Jersey		Oklahoma
	New York		Texas
	Pennsylvania		
		Mountain	Arizona
East North Central	Indiana		Colorado
	Illinois		Idaho
	Michigan		New Mexico
	Ohio		Montana
	Wisconsin		Utah
			Nevada
West North Central	Iowa		Wyoming
	Nebraska		
	Kansas	Pacific	Alaska
	North Dakota		California
	Minnesota		Hawaii
	South Dakota		Oregon
	Missouri		Washington
South Atlantic	Delaware		
	District of Columbia		
	Florida		
	Georgia		
	Maryland		
	North Carolina		
	South Carolina		
	Virginia		
	West Virginia		

Notes: The table lists the states corresponding to the Census Divisions used for our calculations in Figure 3.3 and Table 3.2.

Table 3.4: Destinations of US Manufacturing Exports

	Share of US Exports (%)	
Country	1987	2003
Canada	25.3	19.6
Japan	11.1	7.2
Great Britain	5.8	5.4
Germany	5.4	5.8
France	4.7	3.3
Mexico	3.2	13.9
Korea	3.1	3.2
Australia	2.5	1.9
Taiwan	2.5	2.2
Italy	2.5	1.6
Singapore	2.1	2.5
Netherlands	2.1	2.4
China	1.9	4.1
Hong Kong	1.7	1.7
Venezuela	1.6	.3
Spain	1.4	.9
Saudi Arabia	1.3	.8
Brazil	1.2	1.3
Sweden	1.2	.5
Switzerland	1.1	.8

Notes: The table lists the destination composition of US manufacturing exports by value in 1987 and 2003. Thus, Germany accounted for 5.4% of total US exports in 1987 and 5.8% in 2003. Calculations are done using the UN Commodity Trade and Statistics Database. We present the share for the top 20 destinations in 1987 across the two different years. These countries account for 81.7% of US exports in 1987 and 79.4% in 2003. These figures demonstrate that the composition has remained stable over time. Shares come even closer when excluding Mexico from the analysis. Indeed, the rank correlation amongst the top 40 destinations in 1987 with their respective ordering in 2003 is 88%.

Table 3.5: Intensive Margin

	Starting			
Continuing	1987	1992	1997	2002
1987	1			
1992	0.75	1		
1997	0.58	0.79	1	
2002	0.46	0.58	0.71	1

Notes: The table lists the percentage of exports in each Census of Manufacturers (CMF) year that came from plants that exported in each of the previous Census years, starting in 1987. Thus, only 46% of exports in 2002 came from plants that exported in 1987, 1992, and 1997. Removing any continuous exporting restriction, we find that 57% of trade in 2002 is from plants that export in both 1987 and 2002. Similar to our other figures, estimations are limited to plants with 20 or more employees.

Table 3.6: Determinants of Export Status

Variable	Specification (1)	(2)	(3)	(4)
Exported last year	.420**	.444**	.456**	.385**
	(.007)	(.008)	(.009)	(.028)
Exported last year * $Post_{95}$		-.044**	-.034**	-.032
		(.006)	(.007)	(.022)
Last exported two years ago	.101**	.153**	.161**	.123**
	(.009)	(.013)	(.013)	(.041)
Last exported two years ago * $Post_{95}$		-.094**	-.092**	-.076
		(.016)	(.017)	(.051)
Total Employment	.001	-.002	-.007	.039
	(.012)	(.012)	.013	(.040)
Wages	.025**	.026**	.031**	.030
	(.011)	(.011)	.013	(.039)
Non-production/Total Employment	-.057**	-.06**	-.052**	-.142**
	(.022)	(.021)	.024	(.066)
Changed Product	.001	.001	.001	-.028
	(.001)	(.009)	.011	(.028)
Productivity	.007**	.007**	.009**	.014
	(.002)	(.002)	(.002)	(.009)
Industry Exchange Rate	.021	.028	.041	-.023
	(.039)	(.039)	(.043)	(.151)
Year Fixed Effects	Yes	Yes	Yes	Yes
Overall R^2	.510	.509	.514	.434
Observations	65388	65388	54947	6089

Notes: The table presents the results from estimating equation (3.2) in the text. The dependent variable is a 0/1 indicator for a given plant's export status in the current year. Standard errors are clustered at the plant level and non-exporting related plant-specific characteristics are lagged by one period in all specifications. The coefficient "Exported last year" is an increasing function of the costs of entering foreign markets anew F_0. The coefficient on "Last exported two years ago" is similarly an increasing function of the difference $F_0 - F_R$, where F_R is the cost of re-entering foreign markets after leaving the foreign market one year ago. $Post_{95}$ is an indicator function for the post-1995 part of the sample. The results suggest a modest decline in F_0 and an increase in F_R. Column (1) presents the results from estimating equation (3.2) with no interactions and column (2) contains our baseline results. Column (3) reports results from using a balanced panel. Column (4) restricts the sample to plants in the industries we considered for our structural analysis. ** denotes significance at the 5% level.

Table 3.7: Prior Distributions

Parameters	Priors $N(\mu,\sigma)$
	Profits
ψ_{01} (intercept)	$\psi_{01} \sim N(0,10)$
ψ_{02} (dom. size dummy)	$\psi_{02} \sim N(0,10)$
ψ_1 (exchange rate)	$\psi_1 \sim N(0,10)$
λ_x^1 (root, first AR)	$\lambda_x^1 \sim U(-1,1)$
λ_x^2 (root, second AR)	$\lambda_x^2 \sim U(-1,1)$
$\sigma_{\omega 1}^2$ (variance, first AR)	$\ln(\sigma_{\omega 1}^2) \sim N(0,20)$
$\sigma_{\omega 2}^2$ (variance, second AR)	$\ln(\sigma_{\omega 2}^2) \sim N(0,20)$
υ (foreign elas. premium)	$\upsilon \sim U[-5,5]$
λ_ξ (root, measurement error)	$\lambda_\xi \sim U(-1,1)$
σ_ξ (std. dev., measurement error)	$\ln(\sigma_\xi) \sim N(0,2)$
	Elasticities of Demand
η_i (demand elasticity)	$\ln(\eta_i - 1) \sim N(2,1)$
	Exporting Decision
γ_{s1} (sunk cost, small plants)	$\gamma_{s1} \sim N(0,20)$
γ_{s2} (sunk cost, large plants)	$\gamma_{s2} \sim N(0,20)$
κ (mean, ε_1 & ε_2)	$\kappa \sim N(0,20)$
$\sigma_{\varepsilon 1}$ (st. dev., ε_1)	$\ln(\sigma_{\varepsilon 1}) \sim N(0,20)$
$\sigma_{\varepsilon 2}$ (st. dev., ε_2)	$\ln(\sigma_{\varepsilon 2}) \sim N(0,20)$
	Initial Conditions
α_0 (intercept)	$\alpha_0 \sim N(0,50)$
α_1 (dom. size dummy)	$\alpha_1 \sim N(0,50)$
α_2 (x_1)	$\alpha_2 \sim N(0,50)$
α_3 (x_2)	$\alpha_3 \sim N(0,50)$

Notes: The table presents the priors used for our structural estimations for each industry. The results are presented in Tables 3.8-3.12. We generally choose diffuse priors to allow the data to speak for itself. Variance parameters have log normal distributions to impose nonnegativity. The root of each $AR(1)$ process is bounded on $(-1,1)$ in order to ensure stationarity. An extended description of how we chose these distributions is found in Section 3.4.2.

Table 3.8: Sunk Cost Parameter Estimates

	Panel	
Parameters for Each Industry	1987-1997	1992-2003
Preserved Fruits & Vegetables (203)		
γ_{s1} (sunk cost, small plants)	3.43 (0.35)	2.30 (0.21)
γ_{s2} (sunk cost, large plants)	3.27 (0.33)	2.05 (0.22)
Metal Forgings & Stampings (346)		
γ_{s1} (sunk cost, small plants)	4.65 (0.34)	5.35 (0.92)
γ_{s2} (sunk cost, large plants)	4.53 (0.44)	5.67 (1.05)
Aircraft & Parts (372)		
γ_{s1} (sunk cost, small plants)	2.10 (0.43)	2.22 (0.49)
γ_{s2} (sunk cost, large plants)	2.16 (0.45)	1.99 (0.45)
Measuring & Controlling Devices (382)		
γ_{s1} (sunk cost, small plants)	2.84 (0.38)	2.50 (0.54)
γ_{s2} (sunk cost, large plants)	2.54 (0.41)	2.63 (0.64)

Notes: The table presents the sunk cost estimates γ_s for each industry over the time periods 1987-1997 and 1992-2003. Means are presented along with standard deviations in parentheses. Median estimates give similar results. We interpret these results as evidence against the argument that declines in the costs to entering foreign markets have played a significant role in export trends across manufacturing as a whole. Full results for each industry are found in Tables 3.9-3.12.

Table 3.9: SIC 203 Posterior Parameter Distributions (Means & Std Deviations)

	Preserved Fruits & Vegs. (203)	
Parameters	1987-1997	1992-2003
	Profits	
ψ_{01} (intercept)	-2.06 (0.23)	-2.06 (0.27)
ψ_{02} (dom. size dummy)	1.05 (0.30)	1.12 (0.35)
ψ_1 (exchange rate)	0.37 (1.50)	-0.31 (0.75)
λ_x^1 (root, first AR)	0.13 (0.03)	0.43 (0.05)
λ_x^2 (root, second AR)	0.71 (0.02)	0.90 (0.03)
$\sigma_{\omega 1}^2$ (variance, first AR)	0.04 (0.01)	0.53 (0.09)
$\sigma_{\omega 2}^2$ (variance, second AR)	1.36 (0.07)	0.43 (0.09)
υ (foreign elas. premium)	0.03 (0.04)	0.00 (0.04)
λ_ξ (root, measurement error)	0.88 (0.01)	0.84 (0.02)
σ_ξ (std. error, measurement error)	0.22 (0.03)	0.21 (0.02)
	Elasticities of Demand	
η_μ (demand elas., μ across plants)	13.39 (7.31)	12.68 (6.14)
η_σ (demand elas., σ across plants)	11.74 (6.89)	11.78 (6.29)
	Exporting Decision	
γ_{s1} (sunk cost, small plants)	3.43 (0.35)	2.30 (0.21)
γ_{s2} (sunk cost, large plants)	3.27 (0.33)	2.05 (0.22)
κ (mean, ε_1 & ε_2)	0.16 (0.03)	0.09 (0.02)
$\sigma_{\varepsilon 1}$ (std. error, ε_1)	1.72 (0.68)	1.42 (0.22)
$\sigma_{\varepsilon 2}$ (std. error, ε_2)	1.31 (0.54)	0.66 (0.09)
	Initial Conditions	
α_0 (intercept)	11.16 (10.21)	7.27 (6.87)
α_1 (dom. size dummy)	28.87 (18.26)	24.06 (16.18)
α_2 (x_1)	46.34 (26.12)	19.36 (66.10)
α_3 (x_2)	-71.33 (31.19)	32.73 (57.31)
Observations	$N = 112, T = 11$	$N = 101, T = 12$

Notes: The table presents the results from estimating the structural model presented in Section 3.4 for the Preserved Fruits and Vegetables industry (SIC 203) over the time periods 1987-1997 and 1992-2003. We find that the average level of sunk costs associated with entering foreign markets facing this industry γ_s declined somewhat over the period from $\sim$ \$3.3 million to $\sim$ \$2.2 million. Mean estimates of foreign demand elasticities are consistent with the findings in the literature.

Table 3.10: SIC 346 Posterior Parameter Distributions (Means & Std Deviations)

Parameters	Metal Forgings & Stampings (346) 1987-1997	1992-2003
	Profits	
ψ_{01} (intercept)	-1.96 (0.29)	-1.27 (0.26)
ψ_{02} (dom. size dummy)	2.77 (0.38)	2.49 (0.32)
ψ_1 (exchange rate)	0.03 (0.59)	1.07 (0.49)
λ_x^1 (root, first AR)	0.04 (0.28)	0.60 (0.15)
λ_x^2 (root, second AR)	0.92 (0.02)	0.86 (0.05)
$\sigma_{\omega 1}^2$ (variance, first AR)	0.13 (0.07)	0.18 (0.09)
$\sigma_{\omega 2}^2$ (variance, second AR)	0.43 (0.08)	0.31 (0.10)
υ (foreign elas. premium)	0.12 (0.04)	0.41 (0.06)
λ_ξ (root, measurement error)	0.82 (0.02)	0.80 (0.03)
σ_ξ (std. error, measurement error)	0.11 (0.01)	0.13 (0.02)
	Elasticities of Demand	
η_μ (demand elas., μ across plants)	13.26 (6.20)	11.74 (6.84)
η_σ (demand elas., σ across plants)	11.97 (6.45)	8.34 (5.30)
	Exporting Decision	
γ_{s1} (sunk cost, small plants)	4.65 (0.34)	5.35 (0.92)
γ_{s2} (sunk cost, large plants)	4.53 (0.44)	5.67 (1.05)
κ (mean, ε_1 & ε_2)	0.55 (0.10)	0.92 (0.40)
$\sigma_{\varepsilon 1}$ (std. error, ε_1)	2.35 (0.28)	1.48 (0.54)
$\sigma_{\varepsilon 2}$ (std. error, ε_2)	1.59 (0.47)	4.72 (1.47)
	Initial Conditions	
α_0 (intercept)	34.90 (9.48)	38.60 (19.22)
α_1 (dom. size dummy)	47.67 (4.05)	45.64 (26.12)
α_2 (x_1)	-63.31 (5.19)	47.79 (45.07)
α_3 (x_2)	-30.17 (7.26)	-0.47 (33.91)
Observations	$N = 704, T = 11$	$N = 648, T = 12$

Notes: The table presents the results from estimating the structural model presented in Section 3.4 for the Metal Forgings and Stampings industry (SIC 346) over the time periods 1987-1997 and 1992-2003. We find that the average level of sunk costs associated with entering foreign markets facing this industry γ_s increased somewhat over the period from $\sim$ \$4.6 million to $\sim$ \$5.5 million. Mean estimates of foreign demand elasticities are consistent with the findings in the literature.

Table 3.11: SIC 372 Posterior Parameter Distributions (Means & Std Deviations)

Parameters	Aircraft & Parts (372) 1987-1997	1992-2003
	Profits	
ψ_{01} (intercept)	-0.45 (0.30)	-0.33 (0.35)
ψ_{02} (dom. size dummy)	2.52 (0.43)	2.54 (0.43)
ψ_1 (exchange rate)	-0.06 (1.00)	0.31 (0.49)
λ_x^1 (root, first AR)	0.22 (0.09)	0.40 (0.08)
λ_x^2 (root, second AR)	0.97 (0.01)	0.97 (0.01)
$\sigma_{\omega 1}^2$ (variance, first AR)	0.57 (0.08)	0.41 (0.05)
$\sigma_{\omega 2}^2$ (variance, second AR)	0.16 (0.06)	0.19 (0.04)
υ (foreign elas. premium)	1.82 (0.13)	2.40 (0.39)
λ_ξ (root, measurement error)	0.98 (0.00)	0.98 (0.00)
σ_ξ (std. error, measurement error)	1.14 (0.12)	1.38 (0.26)
	Elasticities of Demand	
η_μ (demand elas., μ across plants)	12.40 (5.44)	12.13 (4.42)
η_σ (demand elas., σ across plants)	12.39 (6.10)	12.25 (5.09)
	Exporting Decision	
γ_{s1} (sunk cost, small plants)	2.10 (0.43)	2.22 (0.49)
γ_{s2} (sunk cost, large plants)	2.16 (0.45)	1.99 (0.45)
κ (mean, ε_1 & ε_2)	0.23 (0.05)	0.18 (0.05)
$\sigma_{\varepsilon 1}$ (std. error, ε_1)	0.83 (0.36)	0.90 (0.25)
$\sigma_{\varepsilon 2}$ (std. error, ε_2)	1.05 (0.29)	0.86 (0.16)
	Initial Conditions	
α_0 (intercept)	50.36 (22.80)	27.68 (16.76)
α_1 (dom. size dummy)	8.85 (18.06)	23.72 (19.60)
α_2 (x_1)	-9.95 (19.15)	-64.19 (26.86)
α_3 (x_2)	-47.56 (57.80)	53.59 (25.83)
Observations	$N = 924, T = 11$	$N = 948, T = 12$

Notes: The table presents the results from estimating the structural model presented in Section 3.4 for the Aircraft and Parts industry (SIC 372) over the time periods 1987-1997 and 1992-2003. We find that the average level of sunk costs associated with entering foreign markets facing this industry γ_s were relatively stable over time. Mean estimates of foreign demand elasticities are consistent with the findings in the literature.

Table 3.12: SIC 382 Posterior Parameter Distributions (Means & Std Deviations)

	Measuring & Controlling Devices (382)	
Parameters	1987-1997	1992-2003
	Profits	
ψ_{01} (intercept)	-0.16 (0.17)	-0.06 (0.17)
ψ_{02} (dom. size dummy)	0.83 (0.24)	1.47 (0.25)
ψ_1 (exchange rate)	-0.83 (0.62)	0.55 (0.45)
λ_x^1 (root, first AR)	0.16 (0.17)	0.61 (0.07)
λ_x^2 (root, second AR)	0.91 (0.03)	0.82 (0.08)
$\sigma_{\omega 1}^2$ (variance, first AR)	0.19 (0.06)	0.31 (0.06)
$\sigma_{\omega 2}^2$ (variance, second AR)	0.16 (0.05)	0.10 (0.06)
υ (foreign elas. premium)	1.36 (0.07)	2.10 (0.13)
λ_ξ (root, measurement error)	0.98 (0.00)	0.98 (0.00)
σ_ξ (std. error, measurement error)	0.84 (0.09)	1.11 (0.18)
	Elasticities of Demand	
η_μ (demand elas., μ across plants)	11.46 (6.68)	10.90 (6.68)
η_σ (demand elas., σ across plants)	8.01 (5.03)	5.88 (3.84)
	Exporting Decision	
γ_{s1} (sunk cost, small plants)	2.84 (0.38)	2.50 (0.54)
γ_{s2} (sunk cost, large plants)	2.54 (0.41)	2.63 (0.64)
κ (mean, ε_1 & ε_2)	0.85 (0.33)	1.43 (0.62)
$\sigma_{\varepsilon 1}$ (std. error, ε_1)	1.48 (0.29)	1.14 (0.51)
$\sigma_{\varepsilon 2}$ (std. error, ε_2)	2.09 (0.81)	4.44 (1.49)
	Initial Conditions	
α_0 (intercept)	40.80 (17.89)	51.39 (21.09)
α_1 (dom. size dummy)	28.84 (25.01)	-5.80 (18.55)
α_2 (x_1)	46.72 (24.20)	0.42 (29.67)
α_3 (x_2)	49.97 (40.25)	64.65 (32.81)
Observations	$N = 1056, T = 11$	$N = 828, T = 12$

Notes: The table presents the results from estimating the structural model presented in Section 3.4 for the Measuring and Controlling Devices industry (SIC 382) over the time periods 1987-1997 and 1992-2003. We find that the average level of sunk costs associated with entering foreign markets facing this industry γ_s were relatively stable over time. Mean estimates of foreign demand elasticities are consistent with the findings in the literature.

Table 3.13: Four Digit Subindustries For Structural Estimations

3 Digit SIC Industry	4 Digit SIC Subindustry
Preserved Fruits and Vegetables (203)	Canned specialties (2032)
	Canned fruits and vegetables (2033)
	Dehydrated fruits, vegetables, and soups (2034)
	Pickles, sauces, and salad dressings (2035)
	Frozen fruits and vegetables (2037)
	Frozen specialties, n.e.c. (2038)
Metal Forgings and Stampings (346)	Iron and steel forgings (3462)
	Nonferrous forgings (3463)
	Automotive stampings (3465)
	Crowns and closures (3466)
	Metal stampings, n.e.c. (3469)
Aircraft and Parts (372)	Aircraft (3721)
	Aircraft Engines and Engine Parts (3724)
	Aircraft Parts and Equipment, N.E.C. (3728)
Measuring and Controlling Devices (382)	Laboratory Apparatus and Furniture (3821)
	Environmental Controls (3822)
	Process Control Instruments (3823)
	Fluid Meters and Counting Devices (3824)
	Instruments to Measure Electricity (3825)
	Analytical Instruments (3826)
	Optical Instruments and Lenses (3827)
	Measuring and Controlling Devices, N.E.C. (3829)

Notes: The table lists the 4 digit 1987 SIC industries that compose the 3 digit 1987 SIC industries that we consider for our structural analyses.

Table 3.14: Evolution of Nontariff Barriers

Category	Tariff Lines Affected (%) 1994	2004
Price Control Measures (antidumping, min import prices)	7	2
Finance Measures (foreign exchange regs)	2	2
Automatic Licensing Measures (prior surveillance)	3	2
Quantity Control Measures (quotas, seasonal prohibition)	49	35
Monopolistic Measures (sole importing agency)	1	2
Technical Measures (requirements for testing, disclosing information, packaging, certain product characteristics)	32	59
Number of Countries	52	97
Number of Tariff Lines	97706	545078

Notes: The figures in the table report the percentage of types of goods (tariff lines) that are affected by each nontariff barrier to trade. They are cited from United Nations Conference on Trade and Development (2005) and support the report's contention that the technical barriers to trade have increased substantially over time.

Figure 3.1: Percentage of US Manufacturing Plants That Export

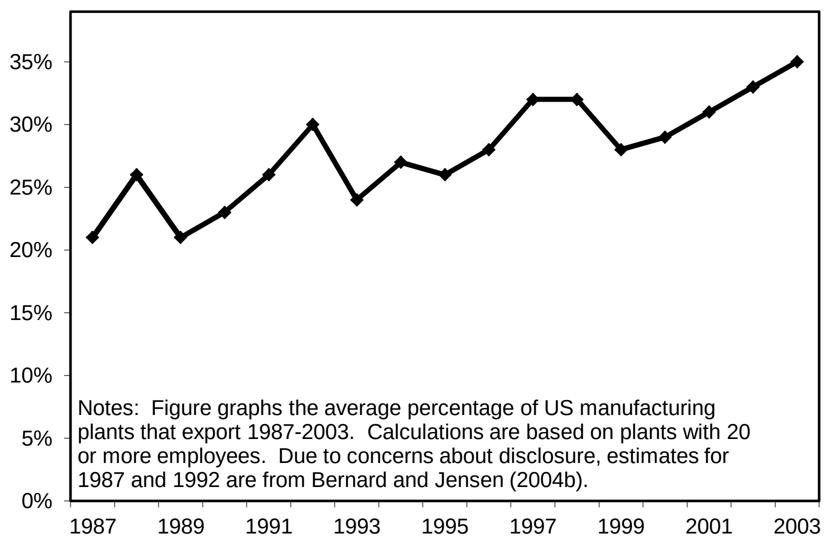


Figure 3.2: Industry Decomposition

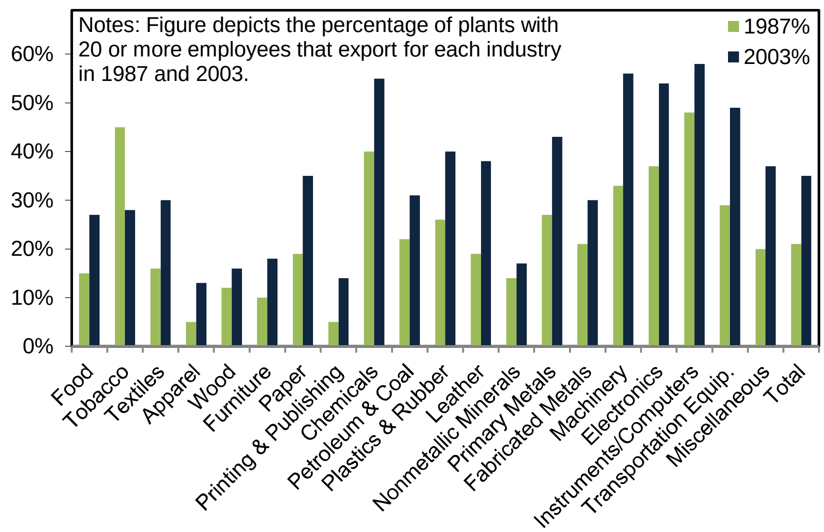


Figure 3.3: Geographical Decomposition

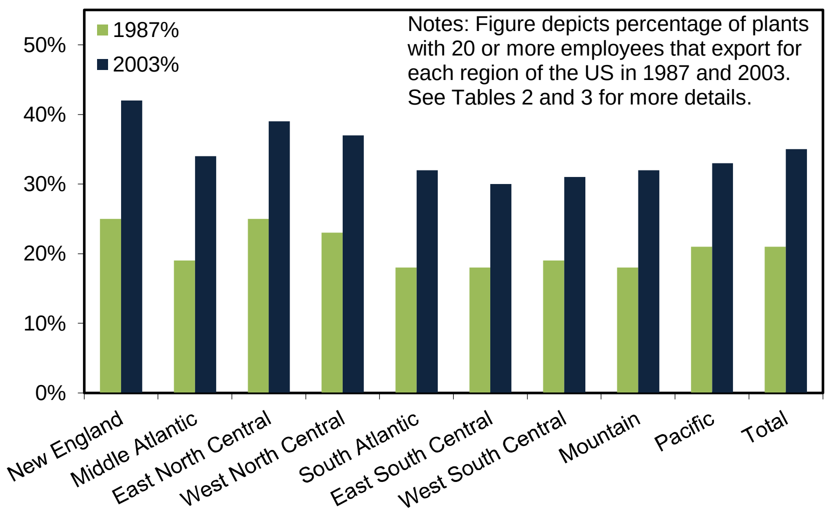
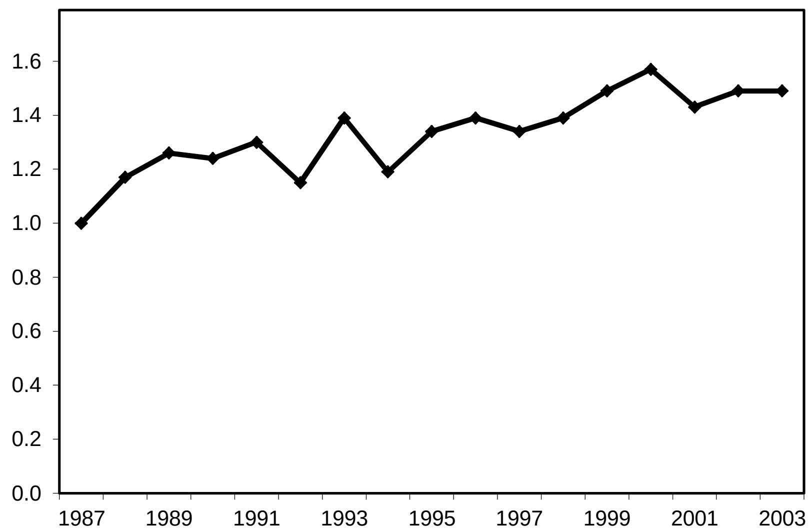
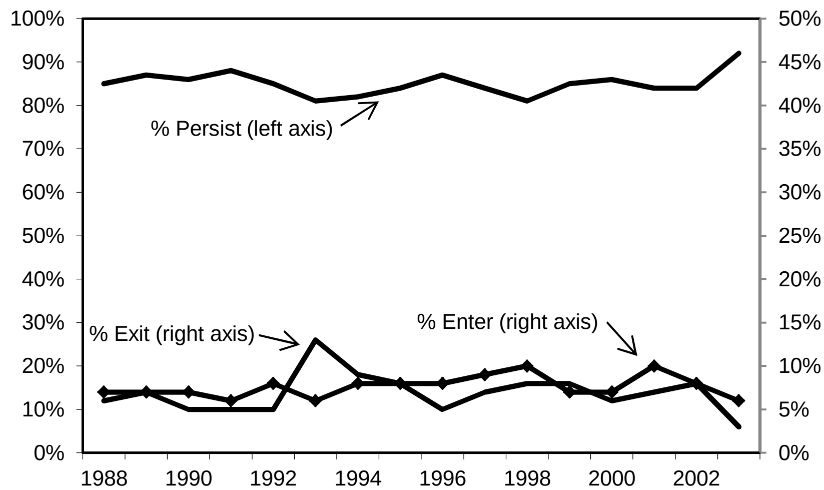


Figure 3.4: Average Foreign Sales Per Exporter



Notes: Figure graphs the average level of real foreign sales per exporter by year 1987-2003. To look at percentage changes, estimates are normalized such that the value in 1987 equals one. Calculations are based on plants with 20 or more employees. We exclude plants in the Computer and Semiconductor industries due to the strong decline in prices over time. Increases in this measure are even stronger when including these industries.

Figure 3.5: Export Persistence, Entries, and Exits



Notes: Figure depicts the annual percent of plants that enter foreign markets, exit, or keep the same export status (domestic or exporter). In each year, the sample is confined to plants that existed in the prior year, such that % Entries + % Exits + % Persist = 100%. Due to changes across ASM sampling frames these figures are limited to plants with 250 or more employees. The exit and entry values for 1988-1992 are from Bernard and Jensen (1999) Table 7 due to disclosure concerns.

CHAPTER IV

The Dynamics of Firm Lobbying

4.1 Introduction

Lobbying is a primary avenue through which firms attempt to change policy in the United States, with total expenditures outnumbering campaign contributions by a factor of nine. While lobbying by businesses is a frequently debated issue in popular discourse, there is little systematic empirical evidence on these behaviors at the firm level.[1] We use a matched data set on firms' lobbying expenditures and operations to study the determinants of firm lobbying over time. We find significant evidence for the existence of up-front costs that are associated with beginning to lobby. These costs affect firms' decisions of whether or not to invest in the political process over time and influence how they react to changes in the policy environment. Moreover, firms that are already lobbying show a significant propensity and ability to adjust their efforts to maximize profits. We hope that our findings will help guide future work in political economy and inform debates over the role of large corporations in influencing policy decisions.

Prior empirical work on firm participation in the policy making process has suffered significantly from data constraints. Most of the available evidence that we

[1]See Ansolabehere, de Figueiredo, and Snyder (2003) and Facchini, Mayda, and Mishra (2011). Recent firm-level exceptions include Igan, Mishra, and Tressel (2011) and Chen, Parsley, and Wang (2010).

do have comes from data on campaign contributions. These contributions often come from Political Action Committees (PACs), which can be set up and organized by firms but which must raise money from voluntary donations from individuals.[2] These studies have addressed such questions as the correlation between political activity and firm size as well as the effect that contributions have on a firm's stock market price.[3] Little work has been done, however, either empirically or theoretically, in looking at the determinants of firm efforts in a dynamic context. With the exception of Facchini, Mayda, and Mishra (2011), the empirical literature on the political economy of international labor movements is also quite thin.[4]

The idea that there are up-front costs to engaging in the political process, however, has a long history. Salamon and Siegfried (1977) cite evidence from Bauer, Pool, and Dexter (1963) to argue that "...firm size is an important determinant of the political activity of executives, since the executives of large firms could afford the luxury of hiring staffs and taking the time to inform themselves about policy issues. What makes the absolute size of available resources, and hence firm size, so important politically is the fact that political involvement has certain fixed costs attached to it..." More recently, Bombardini (2008) has developed a model in which up-front costs affect firms' decisions of whether or not to lobby. She uses data on campaign contributions to demonstrate that her approach fits the data on the industry-level structure of tariffs better than prior models. Grossman and Helpman (2001) also

[2]Direct political contributions by firms were prohibited by the Tillman Act of 1907. A 2010 decision by the Supreme Court in *Citizens United v. Federal Election Commission* granted corporations, unions, and individuals the right to donate unlimited funds to outside groups to campaign for or against candidates. Our discussion of the legal framework for lobbying focuses on the 1998-2006 period that we analyze empirically.

[3]See Grenzke (1989), Grier, Munger, and Roberts (1994), Romer and Snyder (1994), Hansen and Mitchell (2000), Chen, Parsley, and Yang (2010), and Cooper, Gulen, and Ovtchinnikov (2010). Fisman (2001), Faccio (2006), Faccio, McConnell, and Masulis (2006), Fisman, Fisman, Galef, and Khurana (2006), Jayachandran (2006), Bertrand, Kramarz, Schoar, and Thesmar (2011), and Coates (2011) also study politically connected firms.

[4]The literature on the political economy of trade, in contrast, is much further developed theoretically and empirically (e.g., Grossman and Helpman 1994, Goldberg and Maggi 1999, Mitra 1999, Gawande and Bandyopadhyay 2000, Magee 2002, Bombardini and Trebbi 2011).

consider a model in which there are fixed costs associated with lobbying.[5]

To shed light on these issues, we match data on firms' lobbying expenditures with other aspects of their operations. These data exhibit several striking features. The first is that few firms lobby, even in our sample of publicly traded firms—only 10% of the firms in our sample engage in lobbying in one or more years over our sample period of 1998-2006. Lobbying is also strongly related to firm size. This is especially true at the extensive margin of whether or not firms lobby, but less so at the intensive margin of how much firms spend on lobbying once the decision has been made to participate in the process. Finally, we find that lobbying status is highly persistent over time. The probability that a firm lobbies in the current year given that it lobbied in the previous year is 92%.

Given the stability of these facts over time, we consider the idea of whether they are driven by up-front costs that are associated with beginning to lobby. Such costs could include: learning the complex laws about lobbying; educating newly hired lobbyists about the details of the firm's interests, characteristics, and vulnerabilities; developing a lobbying agenda; researching what potential allies and opponents are lobbying for; and investigating how best to attempt to affect the political process (e.g., in which policy makers to invest).[6] To the extent that lobbying represents a legislative subsidy to sympathetic policy makers (Deardorff and Hall 2006), politicians may also require such an initial investment of resources to signal a firm's willingness to support them over time. The qualitative literature on lobbying has long stressed the importance of establishing continuing relationships with policy makers for the effectiveness of lobbying efforts. If the benefits from lobbying then fall dispropor-

[5] This idea was also notably influential to the work of Masters and Keim (1985).

[6] We abstract from the decision to lobby by setting up an in-house lobbying department or by hiring external consultants. While setting up a whole office for in-house operations is likely more expensive, if a firm employs a lobbyist externally the new hire still has to spend a significant amount of time learning the particular needs and characteristics of their new client and how items currently on the agenda will affect them specifically.

tionately on large firms, then only these companies will have the incentive to pay this up-front cost.

To test these ideas, we construct a dynamic empirical model of firm lobbying behavior. This approach implies a reduced form specification for the probability that a given firm lobbies in a particular year. In this model firms have to pay a one-time sunk cost when they begin to lobby. These costs then create an option value associated with continuing to lobby that alters firms' intertemporal decisions. Once firms get in, they tend to stay in because they would prefer not to spend the money to set up a lobbying operation again in the near future. When we take the model to the data, we find strong evidence for the existence of these entry costs. Even after accounting for a number of other factors that would drive firm behavior, we see that these up-front costs exert a significant influence on firm decisions over time.

To further test these predictions, we then look in depth at a specific policy shift that has been the subject of significant public debate: the dramatic decline in the limit on H-1B visas that occurred in 2004. This decline was due to the expiration of prior legislation and offers a special natural experiment (e.g., Kato and Sparber 2011). Constructing a smaller panel of firms that are likely to be responsive to changes in immigration policy, we show that this event precipitated a significant shift in firms' lobbying behavior for those that had lobbied previously for other issues. The manner in which this adjustment occurs indicates little constraint on shifts across issues important for firms. At the same time, we find that changes in the cap had little effect on the extensive margin of lobbying; the decline in the limit on H-1B visas did not induce new firms to lobby. We consider the large shift in the intensive margin relative to that of the extensive margin as corroborating evidence for the existence of these barriers to entry.

Our work contributes to the nascent empirical literature on lobbying and represents one of the first to study lobbying behavior at the firm level. Our results argue that the dynamic nature of lobbying status is a feature that should be included in both future theoretical and empirical work. Selection into lobbying is driven by a number of distinct factors, and studies that fail to address this issue will find biased results. This applies to a wide range of topics, from the impact of lobbying on firm performance to the determinants of trade protectionism. More generally, we contribute to understanding the microfoundations of how political institutions function. Understanding these foundations is crucial for a number of questions in political economy.[7] Entry costs can effectively "fix the players in the game" with respect to the set of firms engaged in the process. These costs can thus influence policy choices by altering the composition of firms that lobby on issues. In particular, the persistence induced by these costs likely allows firms and politicians to be able to predict what groups will work to support or oppose various policy changes. Moreover, stability in this interface between government and firms may induce persistence in political and economic institutions or raise the prospects of regulatory capture.

In the next section we describe our data and a number of features of these data that are suggestive of the existence of up-front costs. We then develop our model of firm behavior and empirical approach in Section 4.3. We present the results from our baseline estimations as well as a number of robustness checks in Section 4.4. Section 4.5 considers evidence on these costs from responses to changes in immigration policy. Section 4.6 concludes and further discusses the implications of the existence of these entry costs.

[7] See, for example, Snyder (1990, 1992), Aghion, Alesina, and Trebbi (2004), Alesina and Rosenthal (1995), and Grossman and Helpman (2001).

4.2 Data and Stylized Facts

Our data come from a number of sources. The primary information on firms' operations comes from Compustat and serves as the platform upon which we build. Information on industry imports comes from the Center for International Data at the University of California at Davis (Feenstra, Romalis, and Schott 2002). Information on lobbying behavior is possible due to the Lobbying Disclosure Act of 1995, which was subsequently modified by the Honest Leadership and Open Government Act of 2007. This act requires individual companies and organizations to provide a substantial amount of information on their lobbying activities. Since 1996, intermediaries who lobby on behalf of companies and organizations have to file semi-annual reports to the Secretary of the Senate's Office of Public Records (SOPR). These reports list the name of each client, the total amount of funds that they have received from each client, and a pre-specified set of general issues for which they lobbied for each client. All firms with in-house lobbying departments are similarly required to file reports, stating their total lobbying expenditures directed towards in-house lobbying activities or external lobbyists. Legislation requires the disclosure not only of the dollar amounts actually received/spent but also for general issues for which the firm lobbied. Tables 4.11 and 4.12 show the list of pre-specified 76 general issues given to each respondent, at least one of which has to be entered. For each general issue, the filer is also required to list the specific issues which were lobbied for during the semi-annual period. Thus, unlike PAC contributions, lobbying expenditures of companies can be associated empirically with very specific, targeted policy areas.[8]

[8] According to the Lobbying Disclosure Act, the term "lobbying activities" refers to "lobbying contacts and efforts in support of such contacts, including preparation and planning activities, research and other background work that is intended, at the time it is performed, for use in contacts, and coordination with the lobbying activities of others." The term "lobbying contact" refers instead to "any oral or written communication (including an electronic communication) to a covered executive branch official or a covered legislative branch official". Further, a lobbyist is "any individual (1) who is either employed or retained by a client for financial or other compensation; (2) whose services include more than one lobbying contact; and (3) whose lobbying activities constitute 20 percent or more of

We compile comprehensive data on lobbying behavior from the websites of the Center for Responsive Politics (CRP) and the SOPR in Washington D.C. Figures 4.6 and 4.7 shows part of the report filed by Microsoft for its lobbying expenditures between January - June 2005. Microsoft lists "immigration" as a general issue and lists "H-1B visas", "L-1 visas", and "PERM (Program Electronic Review Management System)" as specific issues under immigration. Besides immigration, Microsoft also lists eight other issues in this report that are not shown. Given our interest in studying firms' responses to changes in high-skilled immigration policy in Section 4.5, we went through the specific issues listed in each report under the general issue "Immigration" and determined which firms were lobbying for what. The specific issues that are listed are often bills proposed in the U.S. House and Senate. For example, H.R. 5744: Securing Knowledge, Innovation, and Leadership Act of 2006 and S. 1635: L-1 Visa Reform Act of 2004 are bills that we deemed to be relevant for high-skilled immigration.[9] In addition to mentioning specific bills, firms also mention "H-1B visas," "L-1 visas," "high-skilled immigration," and the like in their lobbying reports. We define a firm to be lobbying for high-skilled immigration in any of these cases.[10] For our analysis of firms' responses to changes in immigration policy, we also use data on applications for H-1B visas and the ethnic composition of a firm's workforce. These data are described in Section 4.5.

his or her services during a three-month period." Any person meeting these criteria must register as a federal lobbyist under the Lobbying Disclosure Act.

[9]H.R. 5744, for example, included provisions for increasing the annual H-1B visa cap and revised student visa provisions. Other bills, such as H.R. 4437: Border Protection, Antiterrorism, and Immigration Control Act of 2005 and S.2611: Comprehensive Immigration Reform Act of 2006, are related to immigration but do not include provisions directly related to high-skilled immigration. Bills pertaining to high-skilled immigration are detailed in the Data Appendix available from the authors. One important piece of legislation is H.R. 4818: Consolidated Appropriations Act, which in 2005 exempted up to 20,000 foreign nationals holding a master's or higher degree from the cap on H-1B visas. The bill was signed into law in December, 2004.

[10]Lobbying data consist of semi-annual lobbying disclosure reports and are posted online. Annual lobbying expenditures are calculated by adding mid-year totals and year-end totals. Whenever there is a discrepancy between data on income and expenditures, CRP uses information from lobbying reports on expenditure. With both the lobbying data and the patenting data described later, we invested substantial effort in identifying subsidiaries and appropriately linking them to parent firms. Data in Compustat are based on each company's fiscal year. As discussed below, we lag Compustat data by one year when merging.

One central concern in studying the dynamics of firm lobbying is measurement error in the variable for lobbying status. Under the Lobbying Disclosure Act, lobbying firms are required to provide a good-faith estimate rounded to the nearest $20,000 of all lobbying-related income in each six-month period. Likewise, organizations that hire lobbyists must provide a good-faith estimate rounded to the nearest $20,000 of all lobbying-related expenditures in a six-month period. An organization that spends less than $10,000 in any six-month period does not have to state its expenditures. If lobbying is disclosed in such cases, the figure is reported in the data as zero. Thus as long as a firm spent $10,000 or more, lobbying status will be correctly observed. Looking at the data, average yearly lobbying expenditures for active firms are $475,000. The mean expenditure for a firm the first time we observe them lobbying outside of the start of the sample is $111,000. Median values are $164,000 and $74,000, respectively. These figures indicate that measurement error induced by reporting requirements is likely to be minimal.

We begin by establishing a number of new facts about the lobbying behavior of firms over time. We consider a balanced panel of U.S.-headquartered firms over the period 1998-2006 that have full sales and employment data. This approach allows us to abstract from the decision to take a company public as well as entry and exit into production. The resulting sample contains 3,260 firms and 29,340 observations. Table 4.1 presents a number of descriptive statistics on this sample for all firms, as well as for firms that lobby and those that do not. As mentioned above, when we match these data to our Compustat sample, one of the clearest stylized facts that emerges from these figures is that very few firms lobby. This is striking, as our data only contain publicly traded companies. These firms are by and large quite sizable and thus more likely than private firms to lobby.

We further find that both the intensive and extensive margins of lobbying are related to firm size. The average firm that lobbies sell roughly four times more than firms that do not lobby. Employment and assets are similarly three-and-a-half times and two times larger, respectively. While firms that lobby are only slightly more likely to engage in research and development (R&D), they tend to spend a significantly larger amount on R&D if they do engage in it. These results are consistent with the literature on campaign contributions, reflecting the correlation between lobbying efforts and PAC contributions.[11] Amongst firms that do lobby, there is a correlation of 28% between sales and lobbying expenditures and 19% between employment and lobbying expenditures. The somewhat weaker correlation between firm size and lobbying on the intensive margin relative to that on the extensive margin is suggestive of the existence of barriers to entry. Indeed, if no such barriers existed, we would expect a significantly stronger correlation between firm size and lobbying expenditures on the intensive margin.

Another particularly striking feature of the data is the high degree of persistence of firm lobbying behavior over time. Given that a firm lobbied last year, the unconditional likelihood of lobbying in the current year is 92%. When we look at this figure across industries, we find very similar results, with almost all two-digit NAICS industries having a persistence rate above 80%.[12] This is also true looking across the firm size distribution. Partitioning the data into quintiles using the sales distribution of those that lobby, we find that the level of persistence across each of the categories is above 88%. Considering changes over time, entry and exit appear partly driven by the bi-yearly election cycle. Interestingly, entry seems to happen in the year before

[11]See Tripathi, Ansolabehere, and Snyder (2002), Facchini, Mayda, and Mishra (2011), and Ludema, Mayda, and Mishra (2010).

[12]Igan and Mishra (2011) also find evidence of persistence in lobbying behavior in the case of financial industry lobbyists.

an election, rather than in the year of the election itself. These results suggest that firms may need to invest early in certain political outcomes. Patterns of exit, in contrast, seem to be unrelated to the election cycle.

Figure 4.1 plots the number of total firms lobbying as well as the total number of entries and exits in each year of our sample. Entries and exits are small relative to the overall number of firms lobbying, reflecting the high level of persistence amongst firms. The total number of firms that lobby in our sample increases steadily over time, with entries in each year regularly outnumbering exits. This pattern is consistent with the findings of Blanes i Vidal, Dracaz, and Fons-Rosen (2011), who document that total lobbying expenditures were roughly twice as large in 2006 as they were in 1998. The two facts that (i) lobbying status is highly persistent over time and (ii) lobbying is strongly associated with firm size mean that the intensive margin of lobbying dominates annual changes in lobbying expenditures. Thus, in a typical year 96% of expenditures were made by firms that lobbied in the previous year. Figure 4.2 plots the total amount of lobbying expenditures based on which year firms first began lobbying in the sample. The vast majority of resources spent over time are accounted for by firms that were lobbying at the beginning of the sample, and this remains true even by the end of our sample eight years later. Firms that entered and first lobbied in 1999, for example, account for a small amount of expenditures, even after several years.[13]

[13] We also examined lobbying by associations. Prior work has shown that lobbying through associations tends to be less predominant than individual lobbying. For example, Igan, Mishra and Tressel (2011) show that lobbying expenditures by associations in the financial sector is less than 10% of overall lobbying expenditures. Similarly, Bombardini and Trebbi (2011) look at trade lobbying and show that the fraction of sectors engaging predominantly in individual lobbying is higher than those engaged in lobbying through associations. In our dataset, among the 2000 top lobbyists, only 15% are associations. Lobbying through associations could itself be a response to the existence of fixed costs to entering the political process.

4.3 Model and Estimation Strategy

To test for the existence of up-front costs associated with beginning to lobby directly, we consider a dynamic model of firm behavior. Our approach is akin to the models used in the literature on international trade, particularly that of Roberts and Tybout (1997).[14] The essential logic of the model is that if there are no up-front costs to beginning to lobby, one should expect firms to start and stop lobbying freely. That is, they should optimize based on today's problem and not worry about the future. If there are such costs, however, then there is an option value associated with being involved in the political process that should alter firms' inter-temporal decisions.

We begin by defining $\pi_{it}(p_t, s_{it})$ as the additional profits that firm i could make in year t if it lobbies. This level is dependent on exogenous processes p_t, such as the business cycle and political climate, and firm-level state variables s_{it}, such as the capital stock. In defining $\pi_{it}(p_t, s_{it})$ as the additional profit that a firm could make in period t if it lobbied relative to the state in which it did not lobby, the model is able to accommodate the fact that the firm has other avenues through which it can affect policy outcomes. This allows us to focus on direct lobbying by firms. We assume that once they begin, lobbying firms can alter the amount that they spend costlessly, making π_{it} the profit-maximizing level of additional profits.[15] We further define L_{it} as an indicator variable for whether the firm lobbies in year t. $L_{it}^{(-)} = \{L_{it} \mid j = 0, 1, 2, \ldots, J_i\}$ denotes the firm's lobbying history where J_i is the firm's age and $L_{it}^{(+)} = \{L_{i,t+j} \mid j \geq 0\}$ represents the firm's choice of lobbying activities in the future. The first time that firms lobby, they have to pay a one-time

[14] See also Dixit (1989), Baldwin and Krugman (1989), Bernard and Jensen (2004), Das, Roberts, and Tybout (2007), and Lincoln and McCallum (2011).

[15] We abstract from the precise mechanisms through which lobbying can increase firm profits. For empirical evidence on lobbying and profits at the firm level, see Chen, Parsley, and Yang (2010) and Igan, Mishra, and Tressel (2011).

cost F_0.[16]

In order to account for the possibility that re-entering the process after only a few years of not lobbying is less (or more) costly than entering anew, we define the re-entry cost F_j as the expenditure a firm needs to incur if it stopped lobbying j periods ago and wants to begin again. Relatedly, we define $\tilde{L}_{i,t-j}$ as an indicator for whether the firm last lobbied j periods ago. Using this expression, we can then write the net period t profits for the firm as

$$R_{it}\left(L_{it}^{(-)}\right) = L_{it}\left[\pi_{it}\left(p_t, s_{it}\right) - F_0\left(1 - L_{i,t-1}\right) - \sum\nolimits_{j=2}^{J_i}\left(F_j - F_0\right)\tilde{L}_{i,t-j}\right].$$

Given this expression, we can write the firm's dynamic problem. It selects the sequence $L_{it}^{(+)}$ that maximizes the expected present value of payoffs today subject to the discount rate δ. Thus the firm chooses

$$V_{it}\left(\Omega_{it}\right) = \max_{L_{it}^{(+)}} E_t\left(\sum_{j=t}^{\infty}\delta^{j-t}R_{ij} \mid \Omega_{it}\right).$$

In a dynamic programming context, we can thus write the firm's choice of whether or not to lobby today L_{it} as the value that meets the following condition

$$V_{it}\left(\Omega_{it}\right) = \max_{L_{it}} R_{it}\left(L_{it}^{(-)}\right) + \delta \cdot E_t\left\{V_{i,t+1}\left(\Omega_{i,t+1}\right) \mid L_{it}^{(-)}\right\},$$

where $E_t\left(\cdot\right)$ is the expected future value in period t conditional on the information set Ω_{it}. Using our expression for $R_{it}\left(L_{it}^{(-)}\right)$ from above and comparing the difference in the net benefits between choosing $L_{it} = 1$ versus $L_{it} = 0$, the firm will lobby in the current period if

$$\pi_{it}\left(p_t, s_{it}\right) + \delta\left[E_t\left(V_{i,t+1}\left(\Omega_{i,t+1}\right) \mid L_{it} = 1\right) - E_t\left(V_{i,t+1}\left(\Omega_{i,t+1}\right) \mid L_{it} = 0\right)\right] \geq \quad (4.1)$$

[16]The model can easily be extended to include a cost of exiting. The coefficient on lagged lobbying status, ξ below, would then also be a function of these costs.

$$F_0 - F_0 \cdot L_{it-1} + \sum\nolimits_{j=2}^{J_i} (F_j - F_0) \tilde{L}_{i,t-j}.$$

Here the term $\delta [E_t (V_{i,t+1} \mid L_{it} = 1) - E_t (V_{i,t+1} \mid L_{it} = 0)]$ represents the option value associated with being able to lobby tomorrow without having to pay the up-front entry cost, which is dependent on expectations about future benefits. We can use the expression in (4.1) to derive an estimating equation to test for the existence of up-front costs that are associated with beginning to lobby. In order to simplify notation, we first define

$$\pi_{it}^* \equiv \pi_{it} (p_t, s_{it}) + \delta [E_t (V_{i,t+1} (\Omega_{i,t+1}) \mid L_{it} = 1) - E_t (V_{i,t+1} (\Omega_{i,t+1}) \mid L_{it} = 0)] .$$

This provides an expression for the expected benefits that the firm plans to receive if it lobbies today. We can then write the firm's choice as a binary decision problem

$$L_{it} = \begin{cases} 1 & \pi_{it}^* - F_0 + F_0 \cdot L_{it-1} + \sum_{j=2}^{J_i} (F_0 - F_j) \tilde{L}_{i,t-j} \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

This expression collapses if there are no entry or exit costs, and the firm lobbies if $\pi_{it} (p_t, s_{it}) \geq 0$. That is, the firm decides to lobby solely based on what is most profitable today. If the factors that determine π_{it} are properly accounted for, we should observe an absence of state dependence in lobbying status.

To proceed with estimation, we need to develop an estimate of $\pi_{it}^* - F_0$. These terms are likely to be determined by a number of factors, including firm characteristics such as firm size and industry status as well as external time-varying factors such as the election cycle. We thus parameterize $\pi_{it}^* - F_0$ with the functional form

$$\pi_{it}^* - F_0 \approx \mu_i + X_{it}' \beta + \phi_t + \varepsilon_{it}.$$

The term μ_i controls for unobserved time-invariant characteristics that induce persistence in lobbying. These effects will account for a significant amount of the variation in firms' industry choices and geographic locations. ϕ_t similarly controls for year effects, such as the business cycle and changes in the overall political environment. The term $X_{it}'\beta$ accounts for shifts in firm characteristics, including the logarithms of sales, employees, research and development expenditures, and the level of industry imports. These variables will allow us to account for changes in firm size and issues related to intellectual property rights. We lag these variables by one period to avoid issues of simultaneity. It is worth noting that the variables in $\mu_i + X_{it}'\beta + \phi_t + \varepsilon_{it}$ will affect the firm's choice to lobby based both on how they influence the current level of profits as well as the option value associated with having already established a presence in the policy making process. Thus, even if lobbying may not yield significant returns today, it may be wise to begin lobbying as an investment in future political outcomes.

This approximation then leads to the estimating equation

$$L_{it} = \mu_i + X_{it}'\beta + \xi \cdot L_{it-1} + \zeta_2 \cdot \tilde{L}_{i,t-2} + \zeta_3 \cdot \tilde{L}_{i,t-3} + \phi_t + \varepsilon_{it}, \tag{4.2}$$

where $\xi = F_0$ and $\zeta_j = F_0 - F_j$. Here we assume that re-entry costs are substantively different than F_0 for only three years. Our primary object of interest is the coefficient ξ. If ξ is estimated to be different than zero, our results would suggest that the up-front costs of beginning to lobby are empirically relevant for determining firms' lobbying decisions over time.

4.4 Model Estimation Results

Tables 4.2 and 4.3 present results from estimating the specification in (4.2) with several different approaches. The dependent variable in each regression is the indicator L_{it} for whether or not firm i lobbied in year t. Standard errors are clustered at the level of the firm in all specifications. As a first pass, column (1) of Table 4.2 presents simple correlation results for the firm characteristics most closely associated with lobbying status. The regression includes controls for three-digit NAICS industry, state, and year fixed effects. State and industry fixed effects correspond to the primary one for the firm, although operations may exist elsewhere. Consistent with our results in Table 4.1, we find statistically significant evidence of an association between lobbying status and sales, employment, and research and development expenditures. The level of industry imports, measured at the four-digit level, demonstrate a positive relationship but are not statistically significant.[17]

Our main estimations using the dynamic panel data estimator of Blundell and Bond (1998) are found in columns (2)-(4) of Table 4.2 and in Table 4.3.[18] In each of our specifications, we find evidence in favor of the existence of up-front costs to beginning to lobby. The coefficients on lagged lobbying status are economically important and statistically significant. Controlling for other factors, lobbying in the prior period raises the probability that a firm lobbies in the current period by 88%. Our baseline specification is found in column (2). Interestingly, firm sales are still a statistically significant predictor of firm lobbying status even after controlling for past lobbying status, albeit with a smaller magnitude. In column (3) we include additional controls for prior lobbying status, finding that the costs of re-entering and beginning to lobby again are fairly similar to the costs of entering anew. Column (4) alternatively drops the firm-specific controls $X_{it}'\beta$ in equation (4.2). The results in both columns yield comparable results to the baseline approach in column (2).

[17]We exclude large conglomerate firms in Compustat in our baseline specification due to the difficulty of assigning them to particular industries. Our results are robust to their inclusion by defining these firms as constituting their own industry. Similar to other studies, we code a minimal value of R&D expenditures for those observations with missing or zero values. We find comparable results when excluding this covariate from the estimations.

[18]We use lags of order two as instruments. As a check on the validity of the GMM approach, we considered the specification test suggested by Arellano and Bond (1991). These tests fail to suggest any problems with this approach. Roodman (2006) reviews the estimation of dynamic panel data models at length.

One concern with the approach that we have taken in columns (2)-(4) is whether the specification fully accounts for free-rider behavior in lobbying. Specifically, separately including firm and time fixed effects in our parameterization may miss changes in industry dynamics over time. In columns (1) and (2) of Table 4.3, we test the robustness of our approach to these concerns. Column (1) reports estimations that include a measure of total lobbying expenditures by other public companies in the sample in firm $i's$ three-digit NAICS industry. We include a lagged measure of other-firm industry lobbying, and the results are similar when using a current period measure. In column (2) we include interacted industry-year fixed effects at the two-digit NAICS industry classification level. This will allow us to capture differences in time effects across industries. In both specifications, we find similar results for the coefficient on lagged lobbying status. Including both the measure of other-firm industry lobbying and industry-year fixed effects also yields similar results. Interestingly, the coefficient on lobbying by other firms in the industry is positive; we do not find evidence for lobbying by other firms to crowd out individual lobbying. As an additional robustness check, we found little change in the coefficient on lagged lobbying status when controlling for a firm's within-industry rank in terms of sales or employment over time. This rank is calculated at the two-digit NAICS level. Dropping firms in industries that were the most lobbying-intensive or concentrated in terms of sales also yielded similar persistence in lobbying status.

To get an alternative perspective on these results, we also estimate equation (4.2) with a within fixed effects estimator. This approach is attractive in that it dispenses with some of the assumptions inherent in using the estimator of Blundell and Bond (1998).[19] Given the length of the panel ($T = 9$), however, we expect the coefficient

[19] Bernard and Jensen (2004) discuss the econometric challenges associated with estimating a similar specification in the context of identifying the determinants of export status.

on lagged lobbying status to be biased downward due to the estimation problems raised by Nickell (1981). The results are reported in columns (3) and (4). The first approach considers lagged lobbying status whereas the second includes additional controls for prior lobbying status. While giving a smaller coefficient on lagged lobbying status, both specifications still find statistically significant evidence in favor of the existence of up-front costs associated with beginning to lobby. We also find statistically significant results with the estimator of Arellano and Bond (1991), although these results are more sensitive across variants. Table 4.16 reports the results from a number of these robustness checks.

4.5 Evidence From Immigration Policy

To get a better sense of the nature of these entry costs and how they affect the dynamics of firm lobbying behavior, we next study lobbying related to a particular change in U.S. legislation: the expiration of the expansion of the cap for H-1B temporary work visas that occurred in 2004. Looking at how firms respond to policy shifts offers us another window on the question of whether or not there are barriers to entry for firms that wish to lobby. If these barriers are sufficiently large, the entry costs should discourage firms from beginning to lobby in response to changes in the policy environment. Given the lack of work on the political economy of immigration at the firm level, we begin by describing the institutional environment and policy change in detail and document several stylized facts about lobbying for immigration for the firms in our sample. We then proceed with our main analyses of how firms responded to these policy changes and how these findings corroborate our conclusions from the estimations of the model.

The H-1B is the primary visa that governs temporary high-skilled immigration to the United States for work in science and engineering. Immigrant workers are an important source of science and engineering talent for the United States; in the 2000 Census, immigrants accounted for 24% and 47% of all scientists and engineers with bachelors and doctorate educations, respectively. Immigrant scientists and engineers also accounted for more than half of the net increase in the U.S. science and engineering labor force since 1995 in the Current Population Survey (CPS). Many U.S. firms are very dependent upon immigrants for their science and engineering workers.[20]

Since the Immigration Act of 1990 established the program, there has been a limit to the number of H-1B visas that can be issued per year. While other aspects of the program have remained relatively stable, this limit has changed substantially. The cap has also been the subject of significant public debate and lobbying efforts. Over the period 1995-2006, there were more than 3,000 news articles about the visa cap. Bill Gates and other prominent industry executives have repeatedly testified before Congress in favor of the cap's expansion, while domestic groups opposed to H-1B workers have lobbied strongly against it. Executives of high-tech firms often argue that higher H-1B admissions are necessary to keep U.S. businesses competitive, to spur innovation and growth, and to keep firms from shifting their operations abroad. Detractors, on the other hand, argue that the program displaces American workers, lowers wages, and discourages on-the-job training.

Figure 4.3 plots the evolution of the numerical limit on H-1B visa issuances over time. The cap was initially set at 65,000 visas until legislation in 1998 and 2000 significantly expanded the program to 195,000 visas.[21] These changes expired in

[20] Related papers include Lowell and Christian (2000), Lowell (2000, 2001), Stephan and Levin (2001), Matloff (2003), Zavodny (2003), Borjas (2006), Rosenzweig (2006), Hanson (2009), Hanson, Scheve, and Slaughter (2009), Tambe and Hitt (2009), Mithas and Lucas (2010), Hunt and Gauthier-Loiselle (2010), Kerr and Lincoln (2010), Kato and Sparber (2011), Hunt (2011), Foley and Kerr (2011), Peri (2011), and Borjas and Doran (2011). Freeman (1971) and Ryoo and Rosen (2004) provide classic discussions of the science and engineering labor market.

[21] These two expansions were contained in the American Competitiveness and Workforce Improvement Act of 1998 and the American Competitiveness in the Twenty-First Century Act of 2000. See Reksulak et al. (2006) and Public Law 105-777, Division C, American Competitiveness and Workforce Improvement Law, Section 416(c)(2).

2004, and the cap fell back to 65,000 visas. This limit has been binding since, despite being raised by 20,000 in 2006 through an "advanced degree" exemption. Figure 4.4 similarly plots the number of months that it took to reach the cap in each year. Following Congressional pressure and an audit by the firm KPMG, U.S. Citizenship and Immigration Services (USCIS) started announcing in 2000 when the cap for fiscal year had been reached. Coinciding with the downturn in high-technology sectors in the early 2000s, the cap took 12 months to reach in 2001 and was not reached at all in 2002 and 2003. This changed abruptly, however, in 2004 when the limit fell back to 65,000 visas.

We use the 2004 change in visa allocations to analyze how firms sensitive to the H-1B program adjusted their lobbying behavior at the intensive versus extensive margins. The 2004 change is an attractive laboratory for several reasons. Most important, the expiration offers a natural experiment to study the determinants of lobbying behavior. One of the challenges in the empirical work on lobbying has been to establish a causal link between lobbying behavior and policy changes (e.g., Facchini, Mayda, and Mishra 2011; Igan, Mishra, and Tressel 2011). Our empirical strategy allows us to better isolate a causal link between changes in policy environments and lobbying behavior. The expiration of legislation also isolates changes in policy environments in exogenous ways that are often not possible with the enactment of legislation (e.g., Romer and Romer 2010). In our context, the date of the expiration was set several years before (when the cap was raised), and the issue was not central to firms during the three preceding years due to full or excess visa supply. When the cap returned to the lower limit, firms had strong reasons to believe that lobbying on the H-1B issue could influence policy choices. Firm lobbying was an

The cap is only for new H-1B issuances; applications for renewals for another three years are exempt from this limit. Universities, government research laboratories, and certain nonprofit organizations were exempted from this cap in 2001.

important factor in the increases in the cap level enacted in 1998 and 2000.[22]

Finally, studying this policy experiment offers the advantage that we are able to measure firm sensitivity to high-skilled immigration issues in a precise way that is difficult for many issues. As we discuss next, we use information from each firm's Labor Condition Applications (LCAs) and the ethnic composition of its science and engineering workforce for these measures. These specialized dependencies allow for falsification tests and extensions that may not be feasible for lobbying related to issues where the main determinant is simply firm size. Our expectation is that we should see a significant shift in the intensive margin towards lobbying for high-skilled immigration but little response in the extensive margin if up-front costs for lobbying pose a large enough barrier to entry.

Our first metric of dependency is based upon LCAs. To hire a foreign worker under the H-1B program, an employer must first submit an LCA to the U.S. Department of Labor (DOL). The LCA lists a specific person the firm wishes to hire, and the primary purpose of the LCA is to demonstrate that the worker in question will be employed in accordance with U.S. law. The second step in the application process after the LCA is approved is to file a petition with the USCIS, which makes the ultimate determination about the visa application.[23] While data on the H-1B visa issuances are not available, the DOL releases micro-records on all applications it receives, numbering 1.8 million for 2001-2006. These records include firm names, and we match the firm names on LCA records to the firms in our Compustat database.

[22]Adjustments to the H-1B cap affect firms in important ways, and this impact is likely to be similar in magnitude to many other lobbying efforts (i.e., the issue is important to the firm but the complete fate of the firm does not rest solely on this policy choice). Back-of-the-envelope calculations using the CPS suggest that raising the H-1B cap by 65,000 visas would increase the U.S. science and engineering labor force by about 1.2%, holding everything else constant. This increase would be about half of the median annual growth rate of science and engineering workers, calculated at 2.7% during the period. Kerr and Lincoln (2010) analyze how H-1B population levels affect dependent firms' invention rates.

[23]Different employers can simultaneously seek visas for the same prospective employee, although firms generally make applications only on behalf of committed workers due to the time and legal fees involved. The application fee for a firm with 26 or more full-time employees was $2,320 in 2008.

This provides us a measure of firms' demand for H-1B visas, independent of whether or not a visa is actually granted. Firms seeking a large number of H-1B visas are likely to be very sensitive to the downward adjustment of the cap and have reason to lobby for its expansion.[24]

Our second metric uses information on the ethnic composition of firms' science and engineering employees. Firms that employ many immigrant scientists and engineers are likely to be very sensitive to the H-1B program. To estimate this dependency, we obtained data on each firm's patents and inventors from the U.S. Patent and Trademark Office (USPTO). While we are unable to directly discern immigrant status for inventors, we can discern the probable ethnicities of inventors through their names. The basic approach uses the fact that inventors with the surnames Chang or Wang are more likely to be of Chinese ethnicity than of Hispanic ethnicity, while the opposite is true for Martinez and Rodriguez. We use two commercial ethnic databases that were originally developed for marketing purposes, and the name matching algorithms have been extensively customized for the USPTO data. The match rate is 99% and is verified through several quality assurance exercises.[25] The H-1B program draws primarily from India and China, which account for over half of all visas during our sample period, and the great majority of those related to science and engineering. Firms that employ a large number of Chinese and Indian scientists and engineers are again likely to be very sensitive to the cap's level.

We develop a panel data set of 171 major firms over 2001-2006 for whom we can construct these measures of dependency on the H-1B visa. This period presents an interesting time to study lobbying behavior, as the main identifying variation

[24] LCAs can list more than one potential immigrant employee; the average across our sample is 2.5 employees per LCA record. Our reported results use LCA record counts; we find very similar elasticities and precision when using employee-weighted record counts.

[25] This methodology is further explained in Kerr (2007, 2008) and Kerr and Lincoln (2010). Kerr and Lincoln (2010) also describe the LCA data in further detail.

during the period corresponds to the expiration of the expansion of the H-1B cap expansion in 2004. The time frame is also partially dictated by the availability of LCA and lobbying data. Our sample construction requires that each firm appears in the Compustat database in all six years, is headquartered in the United States, and that it accounts for at least 0.05% of total U.S. domestic patents. Reflecting the extreme skewness of the firm size distribution, this group of 171 firms accounts for more than $3 trillion of worldwide production annually despite the modest size of our sample. Gabaix (2011) notes the particular influence of very large firms on aggregate economic outcomes, and our work continues in this vein to describe their efforts to shape the political process.

Tables 4.4 and 4.5 presents a number of descriptive statistics on these firms. These firms are significantly larger and more likely to lobby overall than our initial sample described in Table 4.1. About 70% of these firms lobby in at least one year over the period 2001-2006, and 20% lobby for immigration. Reflecting the greater share of high-tech firms in this sample, roughly three-quarters of firms that lobby for immigration specifically lobby for high-skill immigration. On average 18% of firms' patents are developed by inventors of Indian and Chinese ethnicity, and the typical firm files for 94 LCA applications annually.[26]

We begin our analysis in Table 4.6. These estimations present simple regression evidence documenting the fact that firms that are more dependent on high-skilled immigration tend to lobby more on this topic. The results are similar when we consider a more generic indicator for lobbying for any immigration-related issue, reflecting the fact that the majority of the firms in our sample that lobby for immigration list high-skilled immigration in the specific issues sections of their reports. The specific

[26]Our core estimations have 846 observations, which is a slight decline from a maximum sample size of 855 observations from crossing 171 firms and five years (once lagging is introduced); the dropped observations are due to missing covariates.

links to our two measures of dependency, however, are sharper for lobbying specific to high-skilled immigration. As a falsification exercise, there are no significant associations between LCA applications or Chinese and Indian patenting and lobbying for non-immigration related issues like Clean Air and Water, Consumer Product Safety, or Retirement.

Figure 4.5 illustrates how firms responded to the cap expiration. It plots the fraction of firms lobbying for high-skilled immigration and the ratio of new H-1B issuances to the cap. These two measures track each other closely, with the fraction of firms lobbying for immigration issues doubling from 6% to 12% between 2003 and 2004. The closeness of these series suggests that lobbying efforts for high-skilled immigration issues intensified once the H-1B cap was reduced in 2004 and became binding again for the private sector. Our data further indicate that these adjustments were significantly larger by firms that were already lobbying. Although only half of the firms that lobbied for high-skilled immigration in 2004 previously lobbied for the issue in 2003, all of them had lobbied for at least one issue in the prior year. Indeed, there is no firm-year observation in our sample in which the firm lobbied for high-skilled immigration and did not lobby in the prior year for some other issue. All of the adjustments among these major patenting firms in response to the policy change were intensive margin adjustments. These patterns are indicative of substantial barriers to entry in lobbying that we found evidence of in the larger Compustat sample.

We consider regression evidence on firms' responses to these policy changes using the specification

$$L_{it} = \mu_i + X_{it}'\beta + \delta \cdot \ln HS_{i,t_0} \cdot CapBinds_t + \phi_t + \varepsilon_{it}. \qquad (4.3)$$

This approach quantifies how firms adjusted their lobbying efforts after the large decline in available visas in 2004, and in particular how this adjustment depends on a firm's dependence on high-skilled immigrants. L_{it} is an indicator function for whether firm i lobbied in year t, X_{it} is a set of firm-level characteristics, HS_{i,t_0} represents a firm's initial dependence on high-skilled immigration, and $CapBinds_t$ equals one for the years 2004-2006 and is zero otherwise. The covariates in X_{it} include the logarithms of firm sales, R&D expenditures, and industry level imports as well as types of technologies patented by the firm and the geographic region of the patented technologies. We lag each of these characteristics by one year to avoid issues of simultaneity, and we find similar results using contemporaneous values or excluding the controls entirely. μ_i denotes a vector of firm fixed effects which controls for unobservable firm-specific characteristics that do not vary over time. ϕ_t accounts for global shocks that affect all the firms equally across different time periods.

The dependencies HS_{i,t_0} can be high, exceeding the shares in the general population. As an example, over 30% of Intel's U.S. patents during this period come from Chinese and Indian workers. We measure our dependencies using 2001 data only so that they are predetermined, initial values at the start of the sample period. The log transformation ensures that outliers in dependency do not overly influence our results. The firm and year fixed effects control for the main effects of the interaction $\ln HS_{i,t_0} \cdot CapBinds_t$. Standard errors are clustered at the cross-sectional level of the firm.

Table 4.7 reports estimations of equation (4.3) for indicators of high-skilled immigration lobbying and lobbying overall. We find strong evidence of a shift in 2004 in lobbying for immigration. Reported results focus on lobbying for high-skilled immigration, and results are similar for overall immigration. Firms with a higher number of LCA applications and greater ethnic patenting by Chinese and Indian inventors in 2001 lobbied more intensively for high-skilled immigration-related issues when the H-1B cap became binding in 2004-2006. A firm with a 10% higher dependence on foreign-born workers is 0.3%-0.4% more likely to lobby for immigration issues during years 2004-2006. At the same time, when we consider overall lobbying status as the dependent variable we find no evidence of extensive margin adjustments to these policy changes. This pattern suggests that the increased lobbying for high-skilled immigration came from firms who were already lobbying adjusting the issues over which they lobbied. We interpret these shifts in lobbying behavior towards high-skilled immigration issues as evidence for adjustments along the intensive margin, which we further investigate below. Consistent with the existence of barriers to entry, these results suggest significant intensive margin adjustments relative to those on the extensive margin.

The intensive margin response is precisely measured. Moreover, the difference in coefficient magnitude between columns (1) and (2) is to be expected, as the LCA metric represents actual demand for H-1B visas while the ethnic patenting measure is more of a general determinant of visa demand. The former measure will be somewhat sharper as visas are used for other occupations like accountants and consultants, too. Reassuringly, these measured effects are also extremely localized to immigration lobbying. Unreported estimations repeat the regressions in columns (1) and (2) for other lobbying issues. Among the twenty top issues on which firms lobby, the only other issue with an economically or statistically significant coefficient when using the LCA dependency is Science/Technology, which is understandable given its link to the H-1B program. Only two issues are linked to the ethnic patenting measure: Consumer Issues/Safety/Protection with a positive elasticity and Financial Institutions/Investments/Securities with a negative elasticity. These cases appear spurious. Overall, this is a very localized response given that these twenty top issues include lobbying on other labor issues (e.g., unions), patent policy, and trade.

Table 4.8 further explores firms' intensive-margin adjustments. We restrict the sample to those firms which lobbied for at least one issue in every year. The results shown in columns (1) and (2) are very similar to those in Table 4.7. This confirms that new firms did not enter into lobbying in response to the policy change. We instead find that all of the response comes from existing firms who have already undertaken the set-up costs (e.g. establishing an in-house lobbying department, establishing contacts with legislators) commencing lobbying for high-skilled immigration issues. These results are consistent with our findings in Section 4.4.

Columns (3) and (4) take this test one step further. The model in Section 4.3 suggests that if a firm is already lobbying, it adjusts the amount and direction of the lobbying it conducts freely and in a profit-optimizing manner. This would suggest that once a firm is lobbying, it should shift to lobbying for high-skilled immigration if it is important to the firm independent of the overall size of the firm's lobbying efforts. Some firms like General Electric and Microsoft lobby the government on many issues. Over the 2001-2006 period, more than 70 firms in our sample lobbied on at least ten issues in one year, and 11 firms lobbied on 25 or more issues at once. It follows that the elasticity of response among lobbying firms should depend only on the importance of the H-1B issue, and not on the scale of overall lobbying activity. A firm only lobbying on a few issues should adjust as much as a similarly dependent firm lobbying on many issues.

We test this prediction in columns (3) and (4) among the firms that always lobby. We create an indicator variable for a firm being above or below the median 2001 lobbying expenditures for this group of firms that always lobbies. We then interact our core regressors with this indicator variable. The main effects now quantify the response evident among firms that always lobby but conduct smaller amounts of lobbying than their peers. The interaction quantifies the differential effect for firms that conduct the greatest lobbying efforts. At the bottom of the table, we provide the linear combination of these two coefficients, which represents the total elasticity for the upper half of the sample. In the LCA case, the elasticity declines slightly in the upper half, while the elasticity rises slightly in the ethnic patenting case. Both differences, however, are extremely small and have t-statistics less than 0.5. The same pattern is again evident when using broader lobbying related to immigration. These findings strongly suggest that the choice to lobby on an issue, once lobbying, depends on the importance of the issue and not the overall scale of lobbying being undertaken by the firm. Adjusting the issues for which the firm lobbies appears to be relatively easy.

Tables 4.9 and 4.10 provides a tabular summary of these effects using our two different measures of H-1B dependency. Columns (1) and (2) tabulate traits where we split firms into ten groups based upon (*i*) whether they lobbied or not in the 2001-2003 period and (*ii*) the strength of their LCA demand. The latter is measured as quintiles based upon each firm's average LCA usage during the sample period. Columns (3) and (4) provide a similar decomposition using the ethnic patenting based dependency. Panel A describes the observation count in each bin. By definition, there are an equal number of firms in each dependency quintile, but the share of firms that lobbied during 2001-2003 is not restricted to be the same. Firms with the lowest dependencies are fairly evenly split on whether or not they lobbied in 2001-2003, while the share lobbying in 2001-2003 increases substantially in the highest dependency bins. Panel B gives the average values of the dependency metric in each bin. These dependencies increase as one moves down the quintile bins, and the dependencies within each row are very similar between firms that lobbied in 2001-2003 versus those that did not. This pattern is by construction and gives a sense of the relative importance of the high-skilled immigration topic across bins.

Panel C of Table 4.10 gives the share of firms that lobby at least once during the 2001-2003 period on high-skilled immigration issues. By definition, these shares are zero for the firms that did not lobby at all during 2001-2003. Among those that did lobby on at least one issue, the share lobbying on high-skilled immigration is very small until it jumps to over 25% in the highest dependency quintile. Panel D provides the share lobbying on high-skilled immigration in at least one year during the 2004-2006 period after the cap becomes binding. The picture is striking: among firms that did not lobby in 2001-2003, there is virtually no entry into high-skilled immigration lobbying. On the other hand, some firms who lobbied during 2001-2003 on other issues start lobbying on high-skilled immigration even though their dependency is very low. Looking back at Panel B, this latter group has only 2%-3% of the dependency of the firms in the highest quintile who had not lobbied before and continued to not lobby (e.g., 4.2 vs. 127.6 and 2.4 vs. 103.5). The final set of rows confirm this. Panel E tabulates the fraction of firms who start lobbying for high-skilled immigration topics during 2004-2006; this share is calculated over the pool of firms in each bin who did not lobby on high-skilled immigration topics during 2001-2003. Looking down the rows in Panel E, entry is closely tied to dependency; comparing the column pairs, entry depends strongly on prior lobbying efforts.[27]

[27]The one firm that began lobbying in 2004-2006 for high-skilled immigration that did not lobby on any issue in 2001-2003 is Nike. Nike began lobbying in 2004 with five issues not related to immigration (e.g., sports, trade). Nike began lobbying on high-skilled immigration in 2005. There are no cases where a firm lobbied for high-skilled immigration during 2001-2003 and stopped lobbying for the topic during 2004-2006.

Firms are not required to list the amount they spend for specific topics. One measure of intensity is the number of years that specific topics are listed by firms, and the patterns using this metric provide a similar story. Of the ten firms that lobbied on high-skilled immigration topics during 2001-2003, only Motorola lobbied for the topic in more years during 2001-2003 than in 2004-2006 (three years vs. two years). Texas Instruments is the only firm reporting

This lack of a response along the extensive margin, along with the strong intensive margin adjustments, demonstrates that barriers to entry played a significant role in shaping how firms responded to these policy changes. If the costs to beginning to lobby had not played a substantial role, we would have expected significant adjustments along the intensive margin as well as the extensive margin for dependent firms. This further suggests that these costs also play a large role in shaping the responses of firms to changes in the political environment.

While not our central focus, these results also shed light on a debate within the political economy literature. Some authors have suggested that lobbyists are specialists that focus primarily on a particular set of issues. An alternate view is that lobbyists can influence a wide range of issues, within the constraints of whom they know. Our results suggest that firms can shift the set of issues that they lobby for relatively easily. This provides suggestive evidence for the 'access' hypothesis as opposed to the 'expertise' hypothesis. These results are consistent with the relatively low levels of persistence in which issues firms lobbied for in our larger firm sample as well as the recent work of Bertrand, Bombardini, and Trebbi (2011) and Blanes i Vidal, Dracaz, and Fons-Rosen (2011).

4.6 Conclusions

While lobbying has been the subject of intense debate in the recent past, there is little systematic empirical evidence on lobbying behavior at the firm level. Our work makes a contribution towards filling this gap. In our panel of publicly-traded, U.S.-headquartered firms over the period 1998-2006, three stylized facts emerge: (i)

lobbying for high-skilled immigration in every year; eight firms lobbied for high-skilled immigration in every year during 2004-2006. When looking among firms that began lobbying regarding high-skilled immigration in 2004-2006, the dependency level of firms lobbying in all three years is ten-fold higher than the dependency level of firms that lobby for the topic in one or two years.

few firms lobby, (ii) lobbying is strongly associated with firm size, and (iii) lobbying behavior exhibits a high degree of persistence. We develop a dynamic model of firm behavior to rationalize these findings, and show that the existence of entry costs can explain all three findings. Our estimations of the model find significant evidence for the existence of these costs across a number of approaches. Using a different approach, we test for the existence of these barriers to entry by considering a natural experiment in the area of immigration policy—the expiration of the increased cap on H-1B visas that occurred in 2004. Using a panel data set of 171 major firms over 2001-2006 with detailed information on lobbying activities, we find that firms dependent on high-skilled immigration adjusted their lobbying behavior towards immigration-specific issues in response to the shock. While the response was very flexible among firms already lobbying, we do not find adjustments on the extensive margin—i.e., firms that were not lobbying on any issue prior to the shock did not start lobbying in response to the shock.

These results support the existence of significant barriers to entry in the process of lobbying. These costs can substantially limit the extensive margin responses of firms to changes in policy environments. This rigidity due to barriers to entry makes the set of firms engaged in the lobbying process relatively stable over time. These costs can thus influence the policy making process and the choices made through the set of actors that lobby on issues. The composition of firms that are advocating on a specific issue are likely to be a non-representative sample of business interests generally. As the high-skilled immigration case illustrates, the group of lobbyists may not even include the voices of all of the most influenced firms if entry barriers are large enough. Moreover, both firms and politicians will be able to reasonably forecast who will support or oppose certain policies among those already engaged in the lobbying process. This mechanism may induce persistence in political and economic institutions. The limited changes in the set of firms lobbying coupled with the long-term relationships that firms build with policy makers may also raise the prospects of regulatory capture.

A better understanding of the role that firms play in policy determination through their lobbying efforts is an essential research objective. Continuing with the high-skilled immigration example, there are only a handful of studies that consider the role of firms in the immigration process or the consequences of policy choices on those firms. The size of this literature is somewhat surprising given the fact that the H-1B program centers on a firm-sponsored visa: the firm identifies the worker it wishes to hire, applies for a visa on their behalf, potentially applies for a green card on behalf of the worker, and generally has a guaranteed period of time during which the worker is tied to the firm. Not surprisingly, firms attempt to define the rules of these procedures. Moreover, they lobby extensively for the capacity to make as many of these hires as they wish. Our understanding of high-skilled immigration policies requires an appreciation of the firm's roles in policy determination. The same is certainly true, if not more so, in other high profile issues like government support to automobile companies and airlines as well as the strength and scope of regulations on financial services. The existence of entry costs to lobbying—and their impact on firm dynamics and the composition of firms lobbying on policy issues—is an important ingredient for future theoretical and empirical work in this vein.

4.7 Tables and Figures

Table 4.1: Descriptive Statistics for Firm Panel

	All Firms	Non-Lobbying Firms	Lobbying Firms
Annual Sales ($m)	1,823	1,423	5,407
	(8,046)	(7,179)	(12,995)
Annual Employment (k)	8	7	23
	(38)	(37)	(45)
Annual Assets ($m)	4,046	3,726	6,914
	(30,732)	(31,764)	(18,896)
Share of Firms Engaging in R&D (%)	44	43	53
	(50)	(49)	(50)
Annual R&D Exp. ($m)	91	50	1,874
	(462)	(297)	(8,245)
Median Lobbying Exp. ($m)			.164
Average Lobbying Exp. ($m)			.475
			(.892)
Share of Firms that Lobby in a Given Year (%)	6.2		
Share of Firms That Ever Lobby (%)	10.0		
Number of Firms	3,260	2,933	327
Observations	29,340	26,397	2,943

Notes: The sample includes 3,260 firms over 1998-2006 for a total of 29,340 observations. Firm operations data are taken from Compustat. Annual R&D expenditures figures are only for firms that perform some R&D. Median and Average Lobbying Expenditures figures are similarly only for firms that lobby. Dollar amounts are in constant 1998 dollars. Standard deviations are denoted in parentheses.

Table 4.2: Determinants of Lobbying Participation

	OLS (1)	B-B (2)	B-B (3)	B-B (4)
(0,1) Lobbied Last Year		.8848	.8448	.8846
		(.0432)	(.0376)	
(0,1) Last Lobbied			.1557	
Two Years Ago			(.1565)	
(0,1) Last Lobbied			.0693	
Three Years Ago			(.0773)	
Log Sales	.0071	.0046	.0031	
	(.0023)	(.0021)	(.0024)	
Log Employment	.0144	-.0042	-.0010	
	(.0031)	(.0038)	(.0050)	
Log R&D Expenditures	.0065	.0004	-.0004	
	(.0013)	(.0009)	(.0010)	
Log Industry Imports	.0005	.0002	.0006	
	(.0017)	(.0003)	(.0003)	
Firm Fixed Effects	No	Yes	Yes	Yes
State Fixed Effects	Yes	No	No	No
Industry Fixed Effects	Yes	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes

Notes: Regressions estimate the determinants of lobbying participation by publicly-listed U.S. firms. Column 1 uses ordinary least squares and Columns 2-4 use the dynamic panel data estimator of Blundell and Bond (1998). Column 2 is our baseline approach. Estimations in Column 1 include state, industry, and year fixed effects. All other estimations include firm and year fixed effects. Firm-specific characteristics are lagged by one year to avoid issues of simultaneity. Regressions include 26,080 observations from 3,260 firms, are unweighted, and cluster standard errors by firm. Column 3 has 19,560 observations.

Table 4.3: Determinants of Lobbying Participation (Continued)

	B-B (1)	B-B (2)	OLS (3)	OLS (4)
(0,1) Lobbied Last Year	.8766	.8810	.4429	.3385
	(.0427)	(.0434)	(.0232)	(.0279)
(0,1) Last Lobbied				.0347
Two Years Ago				(.0458)
(0,1) Last Lobbied				.0184
Three Years Ago				(.0478)
Log Sales	.0020	.0034	.0005	.0000
	(.0022)	(.0021)	(.0006)	(.0007)
Log Employment	.0017	-.0021	.0016	.0022
	(.0038)	(.0040)	(.0015)	(.0019)
Log R&D Expenditures	-.0010	-.0003	.0010	.0003
	(.0010)	(.0012)	(.0009)	(.0009)
Log Industry Imports	.0001	.0000	.0006	.0003
	(.0003)	(.0010)	(.0007)	(.0008)
Log Lobbying by Other	.0056			
Firms in Industry	(.0024)			
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	No	Yes	Yes
Industry-Year Fixed Effects	No	Yes	No	No

Notes: Regressions estimate the determinants of lobbying participation by publicly-listed U.S. firms. Columns 1-2 use the dynamic panel data estimator of Blundell and Bond (1998) and Columns 3-4 use ordinary least squares. Firm-specific characteristics are lagged by one year to avoid issues of simultaneity. Industry x year fixed effects in Column 3 are defined at the two-digit level of the NAICS industry classification. Regressions include 26,080 observations from 3,260 firms, are unweighted, and cluster standard errors by firm. Column 4 has 19,560 observations.

Table 4.4: Descriptive Statistics for High-Skilled Immigration Panel

	All Firms	Firms Not Lobbying for HS Immigration	Firms Lobbying for HS Immigration
	A. Firm Operations		
Annual Sales ($m)	14,680	11,561	32,073
	(31,725)	(25,555)	(51,334)
Annual Employment (k)	44	38	77
	(67)	(64)	(76)
Annual Assets ($m)	22,604	20,085	36,651
	(65,144)	(68,196)	(41,899)
Annual R&D Exp. ($m)	753	579	1,720
	(1,431)	(1,281)	(1,798)
	B. Patenting Efforts		
Annual Patent Count	236	152	704
	(482)	(222)	(1,001)
Annual US Domestic Patents By Chinese and Indian Inventors	43	24	151
	(99)	(40)	(206)
	C. Immigration Visa Apps		
Annual LCA count	94	49	345
	(258)	(80)	(576)

Notes: The sample includes 171 US-headquartered firms over 2001-2006 for a total of 1,026 observations. A list of these firms is in Tables 4.13-4.15. We collect lobbying efforts from mandated lobbying reports filed with Congress biannually. Patent data are from the United States Patent and Trademark Office. We identify inventors of Chinese and Indian ethnicity through inventor names. Labor Condition Applications (LCA) are an initial step in the H-1B application process. We collect these LCA records from the Department of Labor. Firm operations data are taken from Compustat. Dollar amounts are in constant 1998 dollars and standard deviations are denoted in parentheses.

Table 4.5: Descriptive Statistics for High-Skilled Immigration Panel (Continued)

	Percent of All Firms
Lobbying for Any Issue	62
Lobbying for Any Issue, at least one year	70
Lobbying for Immigration	10
Lobbying for Immigration, at least one year	20
Lobbying for High-Skilled Immigration	7
Lobbying for High-Skilled Immigration, at least one year	15
Average Annual Lobbying Expenditure ($m)	1.3
Median Annual Lobbying Expenditure ($m)	.2

Notes: See Table 4.4.

Table 4.6: Determinants of Lobbying for High-Skilled Immigration Issues

	(0,1) HS Immigration Lobbying			
	(1)	(2)	(3)	(4)
Log Sales	.039	.022	.011	.019
	(.020)	(.018)	(.015)	(.024)
Log Employment	-.011	-.008	-.001	.007
	(.021)	(.019)	(.017)	(.026)
Log R&D Expenditures		.028	-.003	-.005
		(.012)	(.013)	(.019)
Log Industry Imports			-.001	-.006
			(.002)	(.008)
Log US Chinese & Indian Patents			.020	.021
			(.008)	(.009)
Log LCA Applications			.031	.025
			(.013)	(.013)
Controls	Basic	Basic	Basic	Extended

Notes: Estimations consider determinants of lobbying efforts over 2001-2006. Firm-specific characteristics are lagged by one year to avoid issues of simultaneity. Basic controls include year fixed effects. Extended controls further include industry-year fixed effects, controls for types of technologies patented, and controls for geographic regions of patenting activity. Regressions include 846 observations, are unweighted, and cluster standard errors by firm.

Table 4.7: Entry into High-Skilled Immigration Lobbying with Binding H-1B Cap

	(0,1) HS Immigration Lobbying		(0,1) Any Issue Lobbying	
	(1)	(2)	(3)	(4)
(0,1) Binding H-1B Cap x Log LCA Counts in 2001	.043		-.008	
	(.014)		(.009)	
(0,1) Binding H-1B Cap x Log Firm Chinese & Indian Patenting in 2001		.029		-.019
		(.012)		(.014)
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Covariates	Yes	Yes	Yes	Yes

Notes: See Table 4.6. Estimations consider entry into lobbying for immigration issues when the H-1B visa issuances cap became binding for the private sector. Firm dependencies are measured in 2001 and interacted with an indicator variable for sample years when the cap was reached (2004-2006). Main effects are absorbed into the firm and year fixed effects, respectively. Firm covariates include variables reported in Table 4.4 (e.g., lagged sales, lagged R&D expenditures, types of technologies patented, and geographic regions of patenting activity). Regressions include 846 observations, are unweighted, and cluster standard errors by firm.

Table 4.8: Lobbying Adjustments among Persistent Lobbying Firms

	(0,1) High-Skilled Immigration Lobbying			
	(1)	(2)	(3)	(4)
(0,1) Binding H-1B Cap x Log Firm LCAs in 2001	.042		.054	
	(.020)		(.021)	
(0,1) Binding H-1B Cap x Log Firm Chinese & Indian Patenting in 2001		.030		.025
		(.019)		(.019)
(0,1) Binding H-1B Cap x Log Firm LCAs in 2001 x (0,1) Above Median Firm			-.013	
			(.020)	
(0,1) Binding H-1B Cap x Log Firm Chinese & Indian Patenting in 2001 x (0,1) Above Median Firm				.008
				(.022)
Estimated Elasticity for Above Median Firm			.042	.033
			(.021)	(.022)
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Covariates	Yes	Yes	Yes	Yes

Notes: See Table 4.7. Sample is restricted to firms that lobby for at least one issue in every year, for 443 observations.

Table 4.9: Adjustments in High-Skilled Immigration

	LCA Dep.		Ethnic Patenting Dep.	
	Not a 2001-3 Lobbyist	2001-3 Lobbyist	Not a 2001-3 Lobbyist	2001-3 Lobbyist
	A. Observation Count			
Least Dependent	114	96	72	138
2nd Quintile	78	126	108	96
3rd Quintile	72	132	84	120
4th Quintile	72	138	72	132
Most Dependent	24	174	24	180
	B. Average Dependency Measure			
Least Dependent	4.6	4.2	2.2	2.4
2nd Quintile	15.8	14.6	6.9	6.6
3rd Quintile	26.6	29.9	12.5	13.8
4th Quintile	62.1	66.7	26.2	31.3
Most Dependent	127.6	401.3	103.5	172.4

Notes: Table summarizes lobbying dynamics regarding high-skilled immigration. Columns 1 and 2 tabulate traits where we split firms into ten groups based upon whether they lobbied or not in the 2001-2003 period and upon the strength of their LCA demand. The latter is measured as quintiles based upon each firm's average LCA usage during the sample period. Columns 3 and 4 provide a similar decomposition using the ethnic patenting dependency. Panel A provides the observation count in each bin. Panel B gives the average values of the dependency in each group.

Table 4.10: Adjustments in High-Skilled Immigration (Continued)

	LCA Dep.		Ethnic Patenting Dep.	
	Not a 2001-3 Lobbyist	2001-3 Lobbyist	Not a 2001-3 Lobbyist	2001-3 Lobbyist
	C. Share Lobbying for HS Immigration 2001-3			
Least Dependent	.00	.00	.00	.00
2nd Quintile	.00	.00	.00	.00
3rd Quintile	.00	.05	.00	.05
4th Quintile	.00	.04	.00	.05
Most Dependent	.00	.28	.00	.27
	D. Share Lobbying for HS Immigration 2004-6			
Least Dependent	.00	.06	.00	.13
2nd Quintile	.00	.10	.04	.06
3rd Quintile	.00	.14	.00	.05
4th Quintile	.08	.22	.00	.23
Most Dependent	.00	.48	.00	.50
	E. Share Entering For HS Immigration, Not Already Lobbying For It			
Least Dependent	.00	.06	.00	.13
2nd Quintile	.00	.10	.06	.06
3rd Quintile	.00	.10	.00	.00
4th Quintile	.08	.18	.00	.19
Most Dependent	.00	.29	.00	.32

Notes: See Table X. Panel C gives the share of firms that lobby at least once during the 2001-2003 period on high-skilled immigration issues. Panel D provides the share lobbying on high-skilled immigration in at least one year during the 2004-2006 period after the cap becomes binding. Panel E tabulates the share of firms who start lobbying for high-skilled immigration topics during 2004-2006; this share is calculated over the pool of firms in each bin who did not lobby on high-skilled immigration topics during 2001-2003.

Table 4.11: Lobbying Issues

Accounting	Economics/Economic Development
Advertising	Education
Aerospace	Energy/Nuclear
Agriculture	Environmental/Superfund
Alcohol & Drug Use	Family Issues/Abortion/Adoption
Animals	Firearms/Guns/Ammunition
Apparel/Clothing Ind./Textiles	Financial Inst./Investments/Securities
Arts/Entertainment	Food Industry (Safety, Labeling, etc.)
Automotive Industry	Foreign Relations
Aviation/Aircraft/Airlines	Fuel/Gas/Oil
Banking	Gaming/Gambling/Casino
Bankruptcy	Government Issues
Beverage Industry	Health Issues
Budget/Appropriations	Housing
Chemicals/Chemical Industry	Immigration
Civil Rights/Civil Liberties	Indian/Native American Affairs
Clean Air & Water (Quality)	Insurance
Commodities (Big Ticket)	Labor Issues/Antitrust/Workplace
Commun./Broad./Radio/TV	Law Enforc./Crime/Criminal Justice
Computer Industry	Manufacturing
Cons. Issues/Safety/Protection	Marine/Maritime/Boating/Fisheries
Constitution	Media (Information/Publishing)
Copyright/Patent/Trademark	Medical Research/Clinical Labs
Defense	Medicare/Medicaid
District of Columbia	Minting/Money/Gold Standard
Disaster Planning/Emergencies	Natural Resources

Source: Senate's Office of Public Records (SOPR).

Table 4.12: Lobbying Issues (Continued)

Pharmacy
Postal
Railroads
Real Estate/Land Use/Conservation
Religion
Retirement
Roads/Highway
Science/Technology
Small Business
Sports/Athletics
Taxation/Internal Revenue Code
Telecommunications
Tobacco
Torts
Trade (Domestic & Foreign)
Transportation
Travel/Tourism
Trucking/Shipping
Urban Development/Municipalities
Unemployment
Utilities
Veterans
Waste (Hazardous/Solid/Interstate/Nuclear)
Welfare

Source: Senate's Office of Public Records (SOPR).

Table 4.13: List of Firms in Sample

Abbott Laboratories	Bristol-Myers Squibb Company
ADC Telecommunications	Broadcom Corporation
Adtran Inc	Brocade Communications Systems
Affymetrix Inc	Brunswick Corporation
Agere Systems	Cabot Microelectronics
Agilent Technologies	Cadence Design Systems Inc
Air Products and Chemicals	Caliper Technologies
Alcoa Inc	Callaway Golf Company
Align Technology Inc	Caterpillar Inc
Allergan Inc	Ciena Corporation
Altera Corporation	Cirrus Logic Inc
Altria Group	Cisco Systems
Advanced Micro Devices	CNH America
American Express	Colgate-Palmolive Company
Amgen Inc	Conexant Systems
Amkor Technology	Corning Inc
Analog Devices Inc	Cypress Semiconductor
Andrew Corporation	Dana Corporation
Apple Computer Inc	Deere and Company
Applied Materials Inc	Dell
Arvin Meritor Technology	Delphi Corporation
Advanced Technology Materials	Digimarc Corporation
Avery Dennison Corporation	Dow Chemical Company
Baker Hughes	Du Pont
Baxter International	Eastman Chemical Company
BEA Systems	Eastman Kodak Company
Becton, Dickinson and Company	Eaton Corporation
Black and Decker Inc	Ecolab Inc
Boeing Company	Eli Lilly and Company
Borg Warner Inc	Emerson Electric

Table 4.14: List of Firms in Sample (Continued)

Exxon Mobil	Interdigital Technology
Fairchild Semiconductor	Intersil Americas Inc
Federal Mogul Worldwide	International Rectifier
Finisar Corporation	Invitrogen Corporation
First Data Corporation	Isis Pharmaceuticals
Ford Motor Company	ITT Manufacturing Enterprises
FormFactor Inc	Johnson & Johnson
Garmin Limited	JDS Uniphase
Gateway Inc	Kimberly Clark Worldwide
General Electric Company	KLA-Tencor Technologies
Genentech Inc	Lam Research Corporation
General Motors Corporation	Lattice Semiconductor
General Signal	Lear Corporation
Gentex Corporation	Lexmark International Inc
Goodyear Tire and Rubber Company	Lincoln Global Inc
Halliburton Company	Lockheed Martin Company
Harman International Industries	LSI Logic Corporation
Harris Corporation	Masco Corporation
Hill-Rom Services Inc	Mattel Inc
Honeywell International	Medtronic Inc
Hewlett Packard-Compaq	Merck and Company
Hubbell Inc	Micron Technology
Human Genome Sciences Inc	Microsoft Corporation
IBM Corporation	Millenium Pharmaceuticals
IGT	Molex Inc
Illinois Tool Works Inc	Motorola Inc
Imation Corporation	National Instruments
Incyte	National Semiconductor
Integrated Device Technology Inc	NCR Corporation
Intel Corporation	Nike Inc

Table 4.15: List of Firms in Sample (Continued)

Nordson Corporation	Symyx Technologies
Novellus Systems Inc	Synopsys Inc
Nvidia Corporation	Tektronix Inc
ON Semiconductor	Tessera Inc
Oracle Corporation	Texas Instruments Inc
Parker-Hannifin	3Com
Pfizer Inc	3M
Pitney Bowes Inc	Tyco Electronics
Playtex Products Inc	Unisys Corporation
PPG Industries	United Technologies
Praxair S T Technology Inc	United Parcel Service
Proctor and Gamble Company	Visteon
Qualcomm Inc	Weatherford International
Qwest Communications Intl.	Western Digital
Rambus Inc	Weyerhauser Company
Raytheon Company	Whirlpool Corporation
Rockwell Automation Technologies	Wolverine Worldwide Inc
Rohm and Haas Company	Wyeth
Schlumberger Technology	Xerox Corporation
Seagate Technology	Xilinx Inc
Semitool Inc	Zymogenetics
Sepracor Inc	
Shuffle Master Inc	
Silicon Laboratories	
Skyworks Solutions Inc	
Sonoco	
Sprint-Nextel	
Steris Inc	
St Jude Medical	
Sun Microsystems	

Table 4.16: Determinants of Lobbying Status: Robustness Checks

	B-B (1)	A-B (2)	B-B (3)	B-B (4)	B-B (5)
(0,1) Lobbied Last Year	.8848	.5245	.8837	.8749	.8823
	(.0432)	(.1816)	(.0438)	(.0416)	(.0488)
Log Sales	.0046	.0026	.0037	.0035	.0046
	(.0021)	(.0045)	(.0019)	(.0021)	(.0026)
Log Employment	-.0042	-.0098	-.0027	-.0012	-.0076
	(.0038)	(.0168)	(.0035)	(.0039)	(.0049)
Log R&D Expenditures	.0004	-.0030	.0004	-.0012	.0021
	(.0009)	(.0094)	(.0008)	(.0014)	(.0013)
Log Industry Imports	.0002	-.0018	.0005	-.0018	-.0005
	(.0003)	(.0032)	(.0005)	(.0013)	(.0006)
Within-Industry Empl.			-.0014		
Rank (*100)			(.0028)		
Log Lobbying by Other				.0079	
Firms in Industry				(.0038)	
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	No	Yes
Industry-Year Fixed Effects	No	No	No	Yes	No

Notes: See Table 4.2. Columns 1 and 3-5 use the dynamic panel data estimator of Blundell and Bond (1998). Column 2 uses the estimator of Arellano and Bond (1991). Column 3 includes controls for the firm's within-industry employment rank. Column 4 includes firm and industry-year fixed effects as well as a measure of other-firm lobbying within a given firm's industry. The last column performs our baseline estimations but excludes the mining, utilities, information, and finance industries from the analysis.

Figure 4.1: Entries, Exits, & Total Firms Lobbying

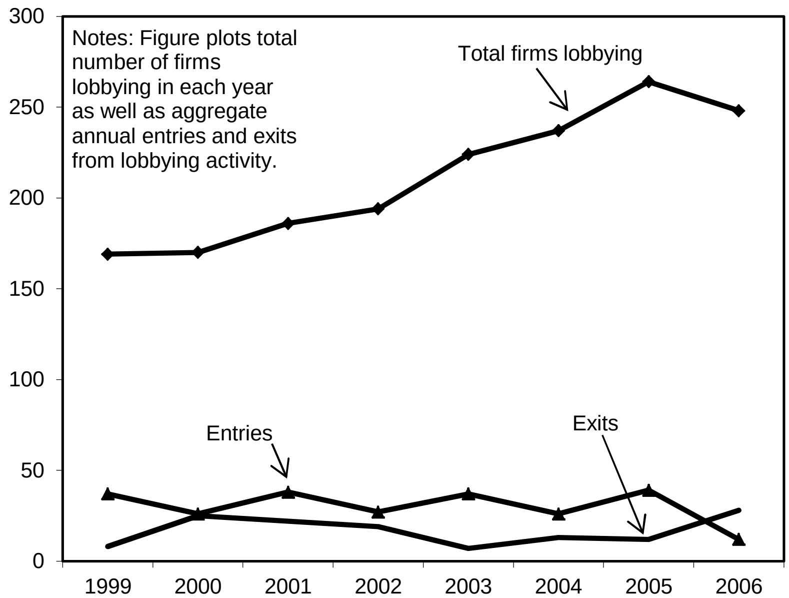


Figure 4.2: Aggregate Annual Expenditures By Entry Cohort

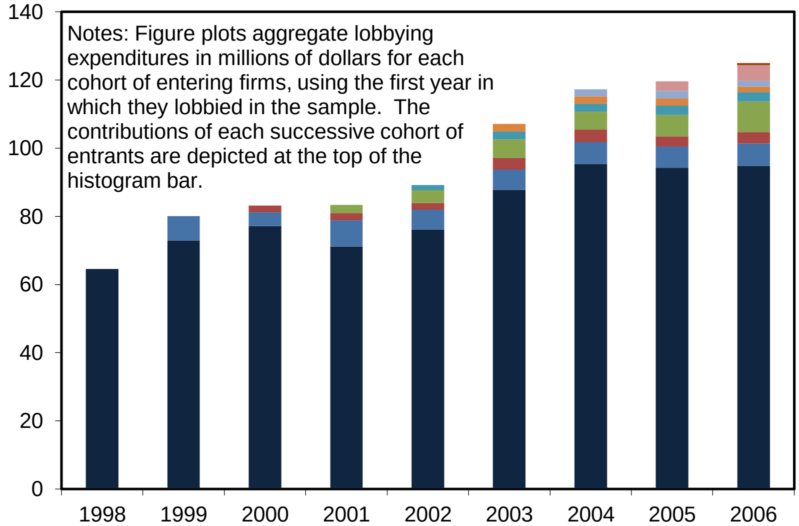


Figure 4.3: Evolution of H-1B Visa Cap

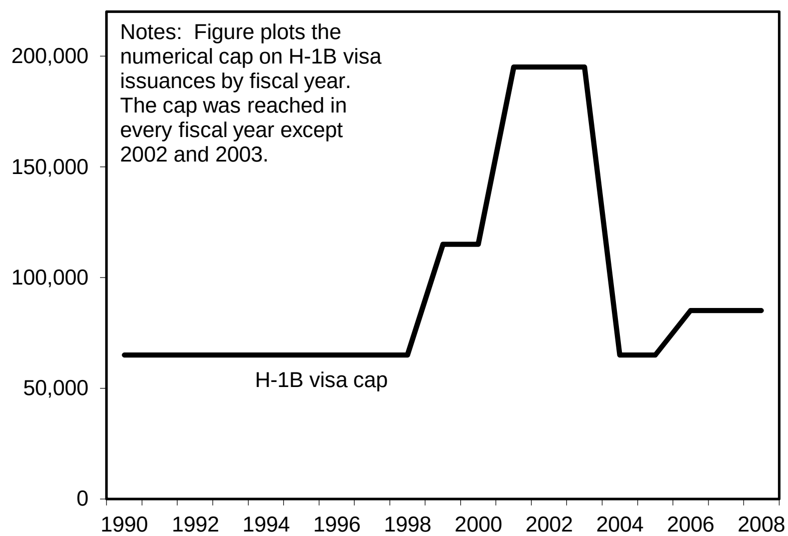


Figure 4.4: Months to Reach H-1B Visa Cap

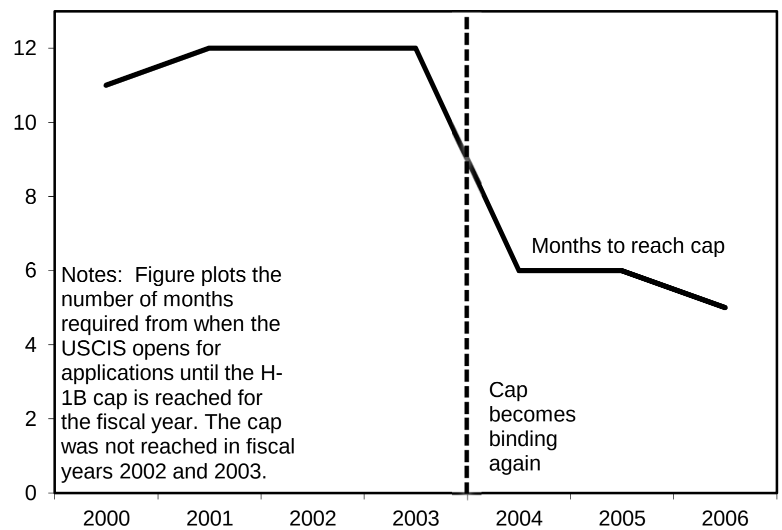


Figure 4.5: H-1B Visas and Lobbying Behavior

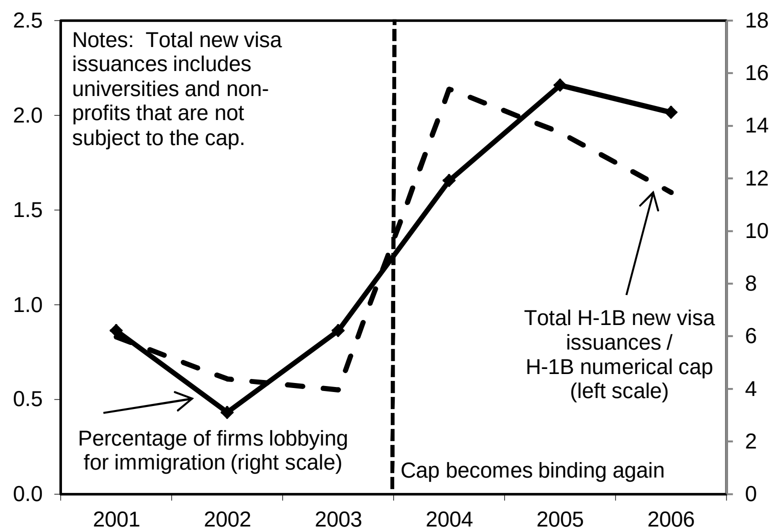


Figure 4.6: Sample Lobbying Report For Microsoft

00000343475

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LOBBYING REPORT

Lobbying Disclosure Act of 1995 (Section 5) - **All Filers Are Required to Complete This Page**

1. Registrant Name
Microsoft Corporation

2. Registrant Address ☐ Check if different than previously reported
Address **1401 Eye Street, NW** **Suite 500**
City **Washington** State/Zip (or Country) **DC 20005**

3. Principal Place of Business (if different from line 2)
City **Redmond** State/Zip (or Country) **WA 98052**

4. Contact Name **Karin Gess** Telephone **(202) 263-5900** E-mail (optional) **kgess@microsoft.com**
5. Senate ID # **25204-12**

7. Client Name ☒ Self
6. House ID # **31174000**

TYPE OF REPORT 8. Year **2005** Midyear (January 1-June 30) ☒ **OR** Year End (July 1-December 31) ☐

9. Check if this filing amends a previously filed version of this report ☐

10. Check if this is a Termination Report ☐ >> Termination Date ________ 11. No Lobbying Activity ☐

INCOME OR EXPENSES - Complete Either Line 12 **OR** Line 13

12. Lobbying Firms	**13. Organizations**
INCOME relating to lobbying activities for this reporting period was:	**EXPENSES** relating to lobbying activities for this reporting period were:
Less than $10,000 ☐	Less than $10,000 ☐
$10,000 or more ☐ >> $ ________ Income (nearest $20,000)	$10,000 or more ☒ >> $ **$4,540,000.00** Expenses (nearest $20,000)
Provide a good faith estimate, rounded to the nearest $20,000 of all lobbying related income from the client (including all payments to the registrant by any other entity for lobbying activities on behalf of the client).	14. **REPORTING METHOD.** Check box to indicate expense accounting method. See instructions for description of options. ☐ **Method A.** Reporting amounts using LDA definitions only ☐ **Method B.** Reporting amounts under section 6033(b)(8) of the Internal Revenue Code ☒ **Method C.** Reporting amounts under section 162(e) of the Internal Revenue Code

Signature ________________ Date **8/12/2005**

Printed Name and Title **Jack Krumholtz - Managing Dir. of Federal Gov't Affairs** Page 1 of 19

Figure 4.7: Sample Lobbying Report For Microsoft (Continued)

00000343484

gistrant Name: **Microsoft Corporation**

Client Name: **Microsoft Corporation**

LOBBYING ACTIVITY. Select as many codes as necessary to reflect the general issue areas in which the registrant engaged in lobbying on behalf of the client during the reporting period. **Using a separate page for each code**, provide information as requested. Attach additional page(s) as needed.

15. General issue area code IMM (one per page)

16. Specific Lobbying issues
H-1B visas
L-1 visas
Program Electronic Review Management System (PERM) regulations

17. House(s) of Congress and Federal agencies contacted ☐ Check if None
Department of Commerce
Department of Labor
Executive Office of the President
House of Representatives
Senate

18. Name of each individual who acted as a lobbyist in this issue area

Name	Covered Official Position (if applicable)	New
Buckner, Marland		No
Corley, Scott		Yes
Gelman, Matt		No
Houton, James		No
Ingle, Ed	White House	No
Krumholtz, Jack		No
Otto, Lori	Senate Republican Policy Committee	No

19. Interest of each foreign entity in the specific issues listed on line 16 above ☒ Check if None

Signature ____________ Date 8/12/2005

Printed Name and Title Jack Krumholtz - Managing Dir. of Federal Gov't Affairs Page 10 of 19

CHAPTER V

Conclusion

The first chapter of this dissertation addresses a major open question in immigration policy by looking at how highly skilled immigrants affect the rate of innovation in a receiving country. This work has since been followed on by further research in the area of immigration and innovation. The second essay addresses how the barriers to entry for exporting to foreign markets have changed over time. To our knowledge, it is the first study to investigate the determinants of the large rise in the number of varieties of goods traded worldwide. In the final chapter we provide evidence on the determinants of firm lobbying. These expenditures represent the primary avenue through which firms attempt to maximize their profits by altering public policy. Our results confirm a long-standing hypothesis in the political science literature, which is that the existence of up-front costs to engaging in the political process help explain the dynamics of firm lobbying behavior.

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