Fewer and Less Skilled?

Human Capital, Competition, and Entrepreneurial Success in Manufacturing

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Abstract: We use micro data on skill levels of establishments to examine the human capital of US manufacturing entrants and incumbent plants over the period 2005-2013. We find a large drop in the cognitive skill levels of the entrant work force over this period. This has serious long-term implications since initial cognitive skills at the establishment level predict future skills and growth rates. While there is a differential decline in entrant skills in industries exposed to Chinese imports, we also find that incumbents upgrade skill levels in exposed industries. High skilled incumbents grow faster than low skilled establishments in exposed industries. The evidence for entrants is weaker, suggesting that they are entering in niches appropriate to their skill sets. The economic effect of import competition on the differential in skills between entrants and incumbents is economically significant explaining between 17%-60% of the skill differential in 2011. Overall, we find that entrepreneurial firms and incumbents are acquiring different skill sets, leaving entrants more exposed to the risk of automation or offshoring.

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Introduction

It is commonly accepted that entrepreneurship is key to economic progress and that the U.S. is especially capable of generating entrepreneurs and providing conditions for the best of them to flourish. Recently, there has been mounting concern that this happy state of affairs is in decay with several business journals pointing out the U.S is creating startup businesses at historically low rates.[1] Several influential papers have found that the rate of entrepreneurial entry has been falling over time and that young firms are no longer generating substantial new jobs, especially in manufacturing.[2]

In this paper, we move beyond the focus on quantity to understanding how the human capital of manufacturing entrants has changed over the period 2005-2013. Specifically we ask whether there has been a decline in high-human capital of entrepreneurial firms, both overall and compared to incumbent firms? We then investigate whether founding skill sets of a firm predicts future skill and success, in terms of growth and survival, over the early life-cycle of a firm.[3] Finally we examine the role of competitive shocks, specifically from Chinese import competition, in the evolution of human capital and the growth of entrepreneurial firms and incumbents. Are competitive pressures changing entrepreneurial firms in all industries or are outcomes in technologically advanced industries different?

To examine these questions, we use administrative establishment level data from the Occupational Employment Statistics (OES) by the U.S. Bureau of Labor Statistics (BLS) that

[1] See "Sputtering Startups Weigh on U.S. Economic Growth; Decades long slowdown in entrepreneurship underscores transition in American labor market" *Wall Street Journal Oct 23, 2016.*
[2] See for example Decker, Haltiwanger, Jarmin, and Miranda (2014), on employment and Pugsley and Sahin (2014) on the decline of entry. The implications for policy have been raised in numerous reports by policy institutes such as the Brookings Foundation, Kaufman Foundation for Entrepreneurship, and the EIG, among others.
[3] We use firm and establishment interchangeably since we are only considering single establishment firms in this paper. For brevity, we also refer to entrepreneurial firms as "entrants."

provides employment and wage data on workers in 800+ occupations in over 1.2 million establishments triennially over the period 2005-2013. We then match our sample firms with firms in the Quarterly Census of Employment and Wages (QCEW) database that enables us to track employment outcomes over time. To measure the firm's skill-level, we use the Department of Labor's Occupational Information Network (O*NET) database to order the occupations from low to high levels in the following six dimensions - Complex Problem Solving (COMPLEXPS), Non-routine Cognitive Analytical (NRCOG), Routine Manual (RMAN), Interacting with Computers (INTERCOMP), Offshoring (OFFSH), and Probability of Computerization (COMPPROB). These six measures capture both the abilities of workers and the nature of tasks in different occupations. We observe each firm's occupational profile, and are thus able to estimate the firm's stock of human capital at various points of time along these six dimensions.

We have the following main findings: First, we find that there has been a drop in the entry of manufacturing firms with over 5 employees over the period 2005-2013. The drop is much greater for large entrants than for smaller entrants. The entry of smallest entrants with below 5 employees has either held level or increased slightly, whereas the fall in the entry rate of the entrants with over 100 employees exceeds 50%. Interestingly, the rate of entry has fallen across the board, in manufacturing and in other sectors of the economy. Within manufacturing we see that the decline is greater in industries facing high Chinese import penetration.

Second, we find that the skill profile of entrepreneurial firms has declined over time. Over the period 2005-2013, the entrants are performing on average tasks requiring lesser cognitive skills. At the same time the entrant workforce is performing higher proportion of routine manual tasks, and these tasks also score at a higher level for being offshored and for the future probability of computerization. The incumbent firms on the other hand do not show the same decline in average skill and there is some evidence to suggest that incumbents are becoming less engaged in routine manual tasks. When we look at changes in manufacturing employment over this period we again find a decline in employment by high skilled entrants. The differences between incumbents and entrants are growing over time.

Third, we show that the initial skill of an establishment strongly predicts the future skill over the next 3 -7 years. Thus, a one standard deviation increase in the entrant's initial percentile rank on cognitive skill predicts that the future skill will be 12-19 percentile ranks higher over the early life-cycle, an economically significant magnitude given that the mean percentile rank in the overall sample is around 50. We find similar economic significance with each of specific skill scores. We also find parallel evidence of persistence in incumbent human capital – the skill level of the incumbent when first observed in the data is very predictive of future skill.

Fourth, we find that for both entrants and incumbents, initial skills predict future growth. Entrants with high cognitive skill scores grow faster. When we look at incumbents, again we find that those with high cognitive skill scores grow faster whereas those with high routine manual scores grow less fast. We do see some evidence of non-linearity in that incumbents with very high initial rank (>90) on Routine Manual skills grow significantly less fast. The growth results for incumbents hold overall and within 4-digit industries. For entrants the results are less robust when controlling for industry, perhaps reflecting the sorting effect of industry choice at entry. We also have some evidence that high skilled entrants and incumbents are less likely to exit especially in low skilled industries.

Finally, we examine the impact of rising competitive pressures due to Chinese trade shocks on both skill and growth of entrants and incumbents. We measure competitive trade shocks by using the change in Chinese import penetration into each 4-digit NAICS manufacturing industry. To isolate the component of U.S. import growth that is driven by export supply growth in China and not by U.S.-specific product-demand shocks, we instrument the change in industry trade exposure using growth in industry imports from China to other high income economies following the strategy in Autor, Dorn, and Hanson (2013).

We find that the differential between entrant skills and those of incumbents is greater in industries exposed to Chinese import completion. The effect is most pronounced in industries that use less skilled labor. Indeed, in high skilled industries we do not observe any changes differential in COMPLEXPS, NRCOG, and INTERCOMP between entrants and incumbents in response to import shocks. One interesting exception is that in high skill industries, but not in low skilled industries, entrants are performing more routine manual tasks than incumbents in response to Chinese import competition.[4]

Overall, these competitive effects on skills are economically significant, suggesting that imports contribute to a 12.7% to 31.3% of the standard deviation decline in average entrant skills relative to that of incumbents over the period 2005-2013. However, even a total cessation in imports would only have cut the differential in 2011 between entrants and incumbent firms and in US manufacturing between 17 to 60%. Thus, Chinese competition is not the primary driver of declining skills of entrants.

We also find that over the period 2005-2013, Chinese import competition causes highly skilled incumbents to grow faster than incumbents with lower skills. We find also find evidence of a similar Darwinian effect among entrants.

[4] We find materially similar results if we were to split industries into low-tech and high-tech industries based on the classification in Goldschlag and Miranda (2016).

Over our sample period there was marked increase in the competition from Chinese imports, and a global financial crisis in 2008-09. As robustness we compute the Chinese import shocks over three separate periods: 2005-2007, 2008-2010, and 2011-2013. We find strong growth effects of initial skill and Chinese import competition for both entrants and incumbents become more evident later in the sample period. That is, incumbents with high initial cognitive skill scores grow faster in industries exposed to Chinese competition whereas those with high routine manual scores grow less fast. These results are stronger for the period 2008-2010 and 2011-2013 compared to 2005-2007, when the level of imports was lower. Skilled entrants grow faster relative to less skilled entrants exposed to Chinese import completion during the crisis period 2008-2010.

One possible explanation for the differences we find between entrants and incumbent firms is that technological advances have changed the optimal mix in manufacturing, so that new plants optimally operate with less skilled workers, whereas incumbent plants are using older technologies that require increased worker skills to operate at higher efficiency. To test for this outcome, we benchmark our sample of entrants against new plants of multi-establishment incumbents. We do not find any declines in the skill levels of these new plants over time, nor are their skill levels affected by Chinese import penetration. Thus, the general decline in the quality of entrepreneurial firms is not the result of competitive pressure on all new plants, but reflects a shift in the comparative advantage of entrepreneurial and incumbent firms.

When we divide industries into those that are highest quintile of cognitive skills and less-cognitively intensive industries, we find that while the rates of entry do not vary across these categories, much of the decline in entrants' skill, and its responsiveness to import shocks has occurred in less cognitively intensive industries.

Overall, we find that there is large drop in the quality of entry in US manufacturing over the period 2005-2013. This drop appears to be only partially due to Chinese import penetration in low technology industries. The drop predicts future lower future levels of human capital for entrants. In general, lower initial human capital predicts lower growth rates, although not lower rates than appropriate for the industries the entrants have entered. There is evidence that in the latter period, 2010-2013, that the Chinese competitive shock causes highly skilled entrants to grow faster than low skilled entrants.

For incumbents, the prior level of human capital predicts future human capital levels and firm growth. However, in contrast to entrants, incumbents do not experience a parallel decline in human capital over the sample period. Moreover, exposure to the Chinese competitive shocks leads them to upgrade human capital and causes more skilled firms to grow faster than less skilled firms.

These outcomes suggest that entrants, particularly in low-technology manufacturing industries exposed to import shocks, find niches that require less skilled labor than incumbent firms. This reallocation occurs both across the manufacturing sector, and also to a lesser extent within 4-digit industries. Thus, there is a separation in the technological choices made by incumbents and entrants, that suggest that in industries exposed to strong import competition in particular these choices may over time cause a bimodal distribution of technological capability.

New firms are considered to account for the bulk of net employment creation (e.g. Adelino, Ma, and Robinson, 2017; Haltiwanger, Jarmin, and Miranda, 2013) and are thus an important population of firms to study. Most of the finance literature has focused on understanding their financing constraints (e.g. Hellman and Puri, 2000; Kerr and Nanda, 2011;

Chemmanur, Krishnan, and Nandy, 2011; Kerr, Lerner, and Schoar; 2011 and Chemmanur and Fulghieri, 2014). In this paper we bring in a new dimension – human capital – to understand the drivers of entrepreneurial success.

Our results contribute to the emerging literature on how founders' education and past experience affect entrepreneurial success. For instance, Gompers, Kovner, Lerner, and Scharfstein (2010), Klepper (2002) and Roberts, Klepper and Hayward (2011) show that entrepreneurial skill, as measured by success in a prior venture or prior relevant work experience, is a big determinant of success.[5] While these papers use past experience as a proxy for entrepreneur skill, in our paper we use direct measures of human capital to obtain estimates of the importance of founder team's initial skills during the early life cycle.[6]

Second, our results contribute to the recent emerging literature on declining entrepreneurship rates in the US. For instance, Pugsley and Sahin (2014) shows that firm startup rates declined from around 13% in the early 1980s to 10% before the Great Recession and eventually 8% by 2012 and they find this pattern to hold in each state, 4-digit industry cell.[7]Few studies have tried to dig deeper to understand what types of entrepreneurship have changed. Decker, Haltiwanger, Jarmin, and Miranda (2014) find that after 2000, there has been a decline in young, high growth businesses. Hyatt and Spletzer (2013) argue that much of the decline in entrepreneurship remains unexplained with general population characteristics such as age of the population and share of workforce with a Bachelor's degree explaining only a small fraction of

[5] Kaplan, Sensoy, and Stormberg (2009) measure human capital at the level of an individual manager and track turnover. Such individual distinctions are tailored to their sample of ex-post highly successful firms. We analyze the broad population of entrants in the US and measure the skill composition of firms.
[6] Other papers have used founding size as a proxy for managerial skill. Ayyagari, Demirguc-Kunt, and Maksimovic (2016) use Indian census data and show that initial size (proxy for initial skills) is a key determinant of how large a firm is during early lifecycle. Maksimovic, Phillips and Yang (2013) show that initial size and productivity predict subsequent acquisition activity and the decision to go public.
[7]Also see Karahan, Pugsley, and Sahin (2015), Decker, Haltiwanger, Jarmin, and Miranda (2014), Davis and Haltiwanger (2014), and Lazear and Spletzer (2013).

the decline in entrepreneurship. In contrast to these papers, we focus specifically on the entrants' skills and how this has changed through time. [8]

Third, our findings add to the debate on the role of competitive trade shocks. On the one hand, a large literature has now shown that surging Chinese imports in US manufacturing has reduced patenting and global R&D expenditure in US manufacturing firms (Autor, Dorn, Hanson, Pisano, and Shu, 2016), hurt manufacturing employment both industry wide (e.g. Pierce and Schott, 2015; Acemoglu, Autor, Dorn, Hanson and Price, 2016), and in local labor markets (Autor, Dorn, and Hanson, 2013), reduced worker incomes (Autor, Dorn, Hanson, and Song, 2014), reduced sales growth and profitability (Hombert and Matray, 2017) and increased plant closures (Bernard, Jensen, and Schott, 2006).

On the other hand, Magyari (2017) looks at firm level data and shows that manufacturing firms exposed to Chinese imports expanded employment and any reduction in employment within some establishments was more than offset by gains in employment in other establishments within the same firms. Bloom, Draca, and Van Reenen (2016) show that import competition led to increases in R&D, patenting within European firms and reallocated employment between firms towards more innovative and technologically advanced firms. In a cross-country context Amiti and Khandelwal (2013) also show that import competition leads to product quality upgrading. We add to this literature in two ways – first we compare incumbents with entrants and see if there is a divergence in their performance. Second we look inside the establishment to look at how the skill level of the workforce is changing with increasing competition.

[8] Hurst and Pugsley (2011) argue that the majority of small entrepreneurs have no expectation to grow or innovate and form new businesses primarily for the nonpecuniary benefits.

Finally, our paper advances a growing literature in corporate finance emphasizing the importance of "managerial fixed effects" for a firm's decisions and performance such as Bertrand and Schoar (2003), Pérez-González (2006), Bennedsen et al. (2007), Malmendier, Tate, and Yan (2011) and Levine and Rubinstein (2017).[9] Others studies document the persistence of dysfunctional managerial styles in firms and posit that the variation in management practices have broader implications for firm growth and productivity differences across countries (Bloom and Van Reenen (2007, 2010), Bloom et. al. (2013)). All these papers focus on managerial characteristics of continuing firms and not on characteristics at the time of startup. The findings in our paper show that the skill set at the time of founding of the firm has a significant influence on how firms perform subsequently. This relates to the corporate imprinting literature (e.g. Baron, Hannan, and Burton (1999)) that argues that founders' visions and backgrounds have an enduring impact on the development of organizational strategy and structure.

II. Data and Summary Statistics

We use establishment-level data from the Occupational Employment Statistics (OES) surveys maintained by the Bureau of Labor Statistics over the period 2005-2013. The OES provides detailed data on the employment and wage rates of workers in each occupation in U.S. establishments. More details on the OES program and the sampling methodology are provided in the Web Appendix. All of our analysis is conducted on establishments that are stand-alone and not identified as belonging to a part of multi-establishment firm. Single establishment firms make up more than 80% of our sample. However in robustness tests we benchmark our results against new plants of multi-establishment firms.

[9] Also see Malmendier and Tate (2008), Schoar and Zuo (2011), Kaplan, Klebanov, and Sorensen, (2012), Cronqvist, Makhika and Yonker (2012), and Graham, Li, and Qiu (2012), , among others.

To this data, we merge information on birth of the firm from the Quarterly Census of Employment and Wages (QCEW), a census of monthly employment and quarterly wage information by 6-digit NAICS industry in the U.S. The birth of the firm is recognized as the date of first non-zero employment. QCEW also allows us to identify firm deaths (establishments that have gone out of business, or have had four consecutive quarters of zero employment) where the date of exit is the date of last positive employment.

We define **Entrants** as all those establishments that are ≤ 2 years of age, i.e. the first time they appear in the OES during the sample period. This is consistent with Klapper, Laeven, and Rajan (2006) who define new firms as all firms below the age of 2. Our results are robust to defining entrants at age 1. For the entrants, we get initial size (size at birth or age 0) and date of birth from QCEW while their initial skill is the first time the establishment is in OES (age≤2). **Incumbents** are establishments that are at least 3 years old when they first appear in our dataset.

We follow the entrants from the time they first appear in our sample period to the end of the sample period (i.e. 2013). Due to the nature of sampling, we have irregularly spaced panel data on skill levels. For growth, we compute an annual establishment growth rate, **Entrant Growth** using employment every 4 quarters from QCEW. **Incumbent Growth** is the annual establishment growth rate calculated for the establishments classified as incumbents in our OES sample. We drop the top and bottom 1% outliers for establishment growth in both the entrant and incumbent samples.

We define four **Size Class** dummies to identify establishments with ≤ 5 employees, 6-20 employees, 21-100 employees and over 100 employees. As Hurst and Pugsley (2011) have pointed out, many small businesses are employment vehicles for skilled professionals and tradesmen rather than firms that "grow and innovate in any observable way." To address this issue, we restrict our analysis to all firms with more than 5 employees but also show how our results change when we look at firms with 5 employees and less.

We restrict all our data to manufacturing firms (NAICS 2007 codes 3111-3399). Within manufacturing we further classify industries into Low-skill and high skill industries based on the median skill value in 2005. As additional robustness, we also classify industries into high-tech industries and low-tech industries based on the classification in Goldschlag and Miranda (2016). More details on this alternate classification are provided in the Web Appendix.

A. *Measures of human capital*

In the OES data, workers are classified into occupations on the basis of the work they perform and skills required in each occupation. The occupations are defined by the Standard Occupational Classification (SOC) system that is designed to reflect the current occupational structure of the U.S. and classifies all occupations in which work is performed for pay or profit.

We capture the skill-level of the establishments using job skills data from O*NET, a database maintained by the Department of Labor that provides data on occupation-specific descriptors that define the key features of an occupation such as worker abilities, technical skills, job output, work activities, etc.

Recent literature has argued that a systematic understanding of labor market trends requires a framework that factors in the allocation of skills to tasks (e.g. Autor, Levy, and Murnane (2003) Acemoglu and Autor (2011, 2012), Costinot, Oldenski, and Rauch (2011), and Keller and Utar, 2016)). These papers argue that the wage polarization of the US labor force is related to skill-based technological change where the returns to highly educated workers performing non-routine cognitive tasks involving decision making, problem solving, and creativity has been increasing.[10]

Following this literature we focus on the following six measures of human capital: COMPLEXPS (Complex Problem Solving) which is identifying complex problems and reviewing related information to develop and evaluate options and implement solutions;

NRCOG (Non-routine Cognitive Analytical skills) from Keller and Utar (2016) which is the sum of Mathematical Reasoning, Inductive Reasoning, Developing Objectives and Strategies, and Making Decisions and Solving Problems;

INTERCOMP (Interacting with Computers) which is using computers and computer systems (including hardware and software) to program, write software, set up functions, enter data, or process information;

RMAN (Routine Manual) from Keller and Utar (2016) which is the sum of Spend time making repetitive motions, Pace Determined by Speed of Equipment, Manual Dexterity, and Finger Dexterity;

OFFSH (Offshorability) from Autor and Dorn (2013) and Firpo, Fortin, and Lemieux (2011) which is the simple average of the two aggregate variables face-to-face contact and on-site job, and the sign of the resulting variable reversed. Face-to-face contact is the average value of the O*NET variables “face-to-face discussions,” “establishing and maintaining interpersonal relationships,” “assisting and caring for others,” “performing for or working directly with the public,” and “coaching and developing others.” On-site job is the average of the O*Net variables

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[10] A related body of work has stressed that differences in managerial skills and practices have significant implications for firm growth and productivity differences across countries (Bloom and Van Reenen (2007, 2010), Bruhn, Karlan, and Schoar (2010), Bloom et. al. (2013)). Hombert and Matray (2017) also show that US manufacturing firms that have invested more in R&D are significantly less affected by trade shocks.

“inspecting equipment, structures, or material,” “handling and moving objects,” “operating vehicles, mechanized devices, or equipment,” and the mean of “repairing and maintaining mechanical equipment” and “repairing and maintaining electronic equipment; As detailed in Autor and Dorn (2013), this measure therefore proxies the extent to which an occupation requires direct interpersonal interaction or proximity to a specific work location.[11]

COMPPROB (Probability of Computerization) from Frey and Osbourne (2016) which provides a measure of whether an occupation is computerisable or not and is in turn based on nine O*NET variables describing computerization bottlenecks such as the level of perception and manipulation, creativity and social intelligence required in each occupation.

Thus COMPLEXPS and INTERCOMP are measures directly from the O*NET database whereas the others are composite measures derived from underlying scales. The Web Appendix provides detailed definitions of each of these variables.

To go from the occupation-level scores to the establishment level, we compute a weighted average across occupations in each firm weighting by the number of employees in each occupation. As a way of identifying the top teams in each establishment, we construct 20 quantiles of the scores and compare the proportion of workers employed in very high skilled occupations (ventiles 15-20) to those employed in very low skilled occupations (ventiles 1-5).

B. Chinese Trade Shock

Following Acemoglu et al. (2016), our main measure of industry exposure to import competition is $\boldsymbol{Imports_j^{US}}$ measured as the total value of Chinese imports into the US in each 4-

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[11] Acemoglu and Autor (2011) caution that offshorability plays a negligible explanatory role in explaining cross-region, cross-industry and cross-national trends in employment and wage polarization (Firpo et al., 2009; Michaels et al., 2009; Autor and Dorn, 2010; Goos et al., 2010) and may be imperfectly measured.

digit NAICS industry j scaled by initial absorption in that industry measured as total industry shipments, $Y_{j,2005}$ plus total imports, $M_{j,2005}$ – total exports, $E_{j,2005}$ in that industry in 2005.

The import penetration ratio for US imports from China has increased exponentially since 2001 when China joined the World Trade Organization (WTO). Figure 1 shows the import penetration ratio for US manufacturing imports from China where import penetration ratio is defined as the ratio of Chinese Imports in manufacturing to US Gross Manufacturing Output + Total Manufacturing Imports – Total Manufacturing Exports. We see that the share of total US spending in manufacturing on Chinese goods has gone up from 4% in 2005 to 6.7% in 2013.

Our identification strategy is derived from Autor, Dorn, and Hanson (2013) and identifies the component of US import growth that is due to Chinese productivity and trade costs. Autor et. al. identify the supply-driven component of Chinese imports by instrumenting the growth in Chinese imports to the United States using contemporaneous composition and growth of Chinese imports in eight other developed countries, $\boldsymbol{Imports_j^{ODC}}$.[12] The identifying assumption underlying this strategy is that the surge of Chinese exports across the world is primarily driven by China-specific events: China's transition to a market-oriented economy and its accession to the WTO and the accompanying rise in its comparative advantage and falling trade costs explains the common within-industry component of rising Chinese imports to the United States and other high-income countries. Thus, by instrumenting, we are addressing reverse causality that may arise if Chinese imports into the U.S. were driven by negative domestic productivity shocks or skill shortages affecting U.S. manufacturers. The Web Appendix provides additional details on the construction of $\boldsymbol{Imports_j^{US}}$ and $\boldsymbol{Imports_j^{ODC}}$ and the strength of the instrument.

[12] Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

Panel A of Table A1 of the Appendix shows the summary statistics for the main variables used in our analysis. Of all the manufacturing establishments in the OES sample from 2005-2013, close to 5% of the establishments are entrants below the age 2 while the rest of the firms are age 3 and older and classified as incumbents. The skill scores in Panel A are the weighted summary statistics of the standardized skill scores at the establishment level. Panel B of Table A2 shows the correlations between the different measures of skill. We see that COMPLEXPS is positively correlated with NRCOG and INTERCOMP and negatively correlated with RMAN and OFFSH. In other words, establishments with high scores on complex problem solving also score high on non-routine cognitive skill and interacting with computers but have low routine manual skills and low offshorability skills. The probability of computerization is positively associated with most other skill scores except for offshorability suggesting that skills sets that require face-to-face contact and on-site work are likely to be computerized in the future, thereby scoring low on the offshoring index.

III. Entry Rates and Quality of Entrepreneurship in US Manufacturing

A growing literature has documented a 30-year decline in various measures of entrepreneurship in the US (e.g. Pugsley and Sahin (2014), Decker et al. (2014), and Hathaway and Litan 2014). An important question to ask is whether we find similar declines in the manufacturing sector or whether it is better or worse off than other major industry sectors in the economy and if there is difference in quality of new firms entering over time.

A. Entry Rates in Manufacturing

We first examine entry in U.S. manufacturing over the period 2005-2013 using data from the QCEW. The entry rate is defined as the number of age 0 establishments in manufacturing with more than five employees as a fraction of the total number of establishments with more than five employees in that year in manufacturing.

Figure 2 shows that over the years 2005-2013, there has been a large decline in entry rates. While there has been rebounding in entry after the 2008 global financial crisis, the entry rate in 2013 is still 5.45% lower than entry rates in 2005. We take this into account in our robustness analyses by splitting our analyses into three periods: pre-crisis (2005-2007), crisis period (2007-2010), and post-crisis (2010-2013). Panel A of Table 1 presents data on entry rates across the major industry groups. We see that the decline in entrepreneurship in the US economy is pervasive across most major industry sectors. We see an increase in entry rates over this period only in the Mining sector.

The entry rates in manufacturing in Figure 2 mask a great deal of variation across size classes, as we show in panel B of Table 1. While firms with less than 5 employees do not seem to be much affected, the decline in entry rates is increasing with the size of entrants with fewer large entrants coming in.

In Figure 3, we compare entry rates into industries that are facing high import penetration from China versus those facing low Chinese import penetration. We define high and low based on the median value of the change in $Imports_j^{US}$ over the period 2005-2013. We see that much of the decline in entry rates in manufacturing is happening in those industries that are facing high import shocks.[13]

[13] In unreported tests of proportions we find that entry rates in the high import industries are significantly different those in low import industries.

Overall, this discussion raises the possibility that the decline in entrepreneurship highlighted by Pugsley (2015) may be accompanied by declines in skill sets and be an indication of a structural shift in the competitive or technological environment, which we now explore.

B. Differences in Skill between Entrants and Incumbents

To examine if there has been a change in the quality of entrants into manufacturing, we first benchmark the skill profile of these entrepreneurs with incumbents of single establishment firms. Since we compare entrants and incumbents within the universe of single establishment firms, our results on establishments in this section are generalizable to all single-establishment firms, which comprise about 80% of all establishments in our data set. In subsequent tests in section V we explore how the skill profile of these entrepreneurs varies when benchmarked against new plants of multi-establishment firms. There we are comparing new against new to see if a stand-alone entrepreneur has a different skill profile than a new establishment of an existing firm.

We begin by examining how the change in the mean skill levels of entrants (age<=2) and incumbent firms vary over our sample period. The labor economics literature has pointed out that over the last twenty years there has been a polarization of jobs in the U.S. economy, with a decline in the share of mid-skilled jobs and increases in low and high skilled jobs (Autor and Dorn, 2013). We examine whether there is a similar U-shaped polarization of entrepreneurial and incumbent enterprises over this period.

In Figure 4, we examine how the employment share and establishment share of entrants and incumbents have changed over the entire sample period for each percentile of initial skill level. We first sort each skill into percentiles by mean skill score in 2005. We then plot the change in each percentile skill's share of total employment from 2005 to 2013 against 2005 skill percentile. We also plot the change in each percentile's share of establishments from 2005 to 2013 against 2005 skill percentile. As standard in the labor literature (e.g. Autor and Dorn, 2013), we smooth the observations using a Lowess smoother with a bandwidth of 0.8.

The first three panels of Figure 4 show that there is a dramatic decline in employment share and establishment share of high skilled manufacturing entrants compared to incumbents along the dimensions of complex problem solving skills, non-routine cognitive analytical skills, and interacting with computers. By contrast, there seems to be an increase in employment share and establishment share of entrants with high routine manual skills and high offshorability over this period while incumbents register a decline in these two skills over this period. For probability of computerization, there seems to be some polarization among entrants with declining employment at the bottom of the distribution and increasing employment at the top of the distribution. Overall, the data show a decline in the use of non-routine cognitive and problem solving skills of entrants, and an increasing reliance on routine manual tasks and tasks that can be offshored. There is no such pattern among the population of incumbent plants.

The summary statistics in Figure 4 suggest that entrants are getting less skilled over time. In Table 2 we compare the skill level of entrants and incumbents over our sample period in a multivariate setting using two specifications that allow us to examine changes over time. In the first specification, in Panel A, we regress skill scores on an interaction of Entrant dummy with year dummies including the main effects and size class dummies. In the second specification, shown in Panel B, we add MSA dummies and 4-digit industry dummies. The specification in Panel A allows us to examine trends in the quality of entrants and incumbents over time, while Panel B shows changes, relative to the industry mean skills and region mean skills. Suppose all the entrants were entering in low skilled industries but at the top of the skill distribution for that industry, panel A might show a declining trend in skills of entrants whereas panel B would show that the entrants are entering at the top of the skill distribution in their industry.

Since we omit the smallest firms in these specifications, the omitted size class dummy is 100+ employees. All regressions include sampling weights and cluster standard errors by MSA. In unreported tests we find similar results when we cluster by industry or two way-clustering by MSA and industry (Cameron, Gelbach, and Miller (2011)).

Panel A shows that over time the interaction of entrant dummy with year dummies becomes negative and significant, especially from 2010 in columns 1-3 suggesting that entrants are less skilled than the incumbents in COMPLEXPS, NRCOG, AND INTERCOMP at least during the later years. The entrant dummy itself indicates that initially (in 2005) the skill levels of the entrants are not significantly different from incumbent single-plant firms.

Columns 4 and 5 show that entrants have higher scores on routine manual skills and offshoring during later years compared to incumbents whereas column 6 does not show significant differences between entrants and incumbents with respect to the probability of computerization.[14] Figure 5 shows the predictive margins of interaction effects of the year and entrant dummies in panel A of Table 2. The first panel of Figure 5 shows that entrants have clearly declining COMPLEXPS, NRCOG, and INTERCOMP skills over time compared to incumbents. For instance for the entrant with median skill in 2005, 16% of the employees were in occupations that scored in the bottom 10 ventiles of COMPLEXPS and the remaining 84% were in the top 10 ventiles of COMPLEXPS. By 2013, for the median skilled entrant, 45% of the employees were in occupations in the bottom 10 ventiles. The second panel of Figure 5 shows that entrants have higher scores on routine manual skills and offshoring and probability of

[14] In Appendix A5 we find no differences between very small entrants and very small incumbents (both with ≤5 employees) along each of these skill dimensions.

computerization though the differences here between entrants and incumbents are less significant. In un-tabulated regressions we find that these effects hold across all size categories of entrant and incumbents above 5 employees.

In panel B of Table 2, we add controls for industry and MSA fixed effects. Columns 1-3 of panel B of Table 2 show that while entrants start out with a higher level of COMPLEXPS and NRCOG in 2005 (entrant dummy is positive and significant in both cases), the interaction of entrant dummy with year dummies is negative and significant for COMPLEXPS, NRCOG and INTERCOMP especially in later years suggesting that entrants are getting less skilled than the incumbents in each of these dimensions. Column 4 shows that entrants have higher scores on routine manual skills over time compared to incumbents whereas columns 5 and 6 do not show significant differences between entrants and incumbents with respect to offshoring and probability of computerization. In unreported tests we find similar results when we cluster by industry or by industry-MSA. Figure 6 shows the predictive margins of these interaction effects.

A comparison of Figure 5 (summary statistics) and Figure 6 shows that by including 4-digit industry fixed effects, the differences between entrants and incumbents are muted. However, overall we still see that entrants in manufacturing are getting less skilled and performing more routine manual tasks over time compared to incumbents. Thus, we see evidence both of a general decline in skills of entrants relative to incumbent firms in manufacturing, and declines relative to incumbents in their industries. [15]

Overall sub-sections A and B have shown us that there is a decline in the quantity, quality, and size of entrepreneurial establishments in manufacturing. In the next two sections we

[15] Due to the irregularly spaced nature of our data, we do not have a true panel dataset of establishment skills and hence we are unable to estimate accurately if there is convergence in the skill of the entrants to the incumbents over time. Hence we focus most of our tests on the initial skill of the establishment.

will examine whether this decline in skill has consequences by examining the effect of the initial skill of these entrants on their future skill and growth.

C. Persistence of Skill

To estimate the effect of initial skill over the early lifecycle of the firm, we first examine whether initial skill scores predict future skill. If it were the case that the skills of new firms were easily readily adjustable over time, then the decline in initial skill of the entrepreneurial establishments may not have serious consequences for the skill profile of these establishments later in their life cycle. However, if initial skill was a firm's destiny in that it is persistent over time and influences future skill, then the importance of initial skills deserves much more emphasis.

Accordingly, we run pooled OLS regressions where we pool all observations across the different time periods for entrants and incumbents separately to predict if initial skill scores of the entrants predict skill scores of the entrant at a future point in time:

$$Skill_{ijt} = \mu + \beta_1 Initial\ Skill_{ij0} + \beta_2 Initial\ Size_{ij0} + \beta_3 Elapsed\ Time_{ijt} + \delta_j \times \gamma_t + \pi_{MSA} \times \gamma_t + \upsilon_{it} \tag{1}$$

where the dependent variable $Skill_{ijt}$ is the future skill score of establishment *i.* Skill could be of one of the following: COMPLEXPS, NRCOG, INTERCOMP, RMAN, OFFSH, and COMPPROB; Initial Size and Initial Skill are defined when the firm is (up to) two years old, μ is the average response across all firms; Elapsed time is the time difference between initial skill and future skill measurements. δ_j are 4-digit NAICS fixed effects, and π_{MSA} are MSA fixed effects, and the υ_{ijt} are random disturbances. Industry x Time fixed effects control for differences in skill across industries due to technology over time and MSA x Year fixed effects control for differences in skill level across regions over time due to factors like financing and clustering. We cluster standard errors in all specifications at the firm level.

A simple scatter plot (Figure 7) of the initial complex problem solving skill and future complex problem for each establishment in the economy from our data shows that the correlation is too noisy to fit a linear regression model. Hence we convert the skill scores into percentile ranks and look at the correlation between initial percentile rank and future percentile rank.[16] So an establishment's percentile rank of complexps, $R_i^{COMPLEXPS}$ in a particular year is based on its position in the distribution of complexps skills in the full sample of manufacturing establishments in that year. Similarly initial percentile rank, $I_i^{COMPLEXPS}$ is based on establishment's position in the year the establishment first appears in the OES sample. Figure 8 presents a binned scatter plot of the mean percentile rank of the establishment $E[R_i|I_i=i]$ vs. their initial percentile rank. The conditional expectation of future rank given initial rank is almost perfectly linear.

Panels A and B of Table 3 presents results for the sample of entrants and incumbents respectively. Both panels show strong evidence of persistence in initial skill levels for entrants and incumbents.[17] A one standard deviation in the initial percentile rank increases future percentile rank of COMPLEXPS by 7.9 percentile ranks for entrants and 9 percentile ranks for incumbents; future percentile rank of NRCOG by 7.5 ranks for entrants and 8.5 ranks for incumbents; future percentile rank of INTERCOMP by 8.2 ranks for entrants and 11.3 ranks for incumbents; future percentile rank of RMAN by 9 ranks for entrants and 10.6 ranks for

[16] A close parallel is Chetty et. al. (2014) who measure intergenerational mobility using correlations between child and parent income percentile ranks.

[17] The number of observations in these panels are much lower because we are using MSA x Year and NAICS4 x Year fixed effects and also dropping the first time the entrant or incumbent appears in the sample because it measures initial skill which is used as our main independent variable of interest in these regressions.

incumbents; future percentile rank of OFFSH by 6.2 ranks for entrants and 8.8 ranks for incumbents; and future percentile rank of COMPPROB by 4.8 ranks for entrants and 8 ranks for incumbents.

In unreported tests for the sample of incumbents we repeat the same specification as in panel B but this time control for MSA x 4-digit NAICS x Year and Elapsed Time fixed effects. The standard errors are once again clustered by firm. Even with the most stringent fixed effects specification of MSA x 4-digit NAICS x Year, we find a strong persistence of initial skills for all six skill-types.

As described in section II, we have irregularly spaced panel data so the observations between the skill measurements could vary anywhere from 12 (3 years) to 46 quarters (or 12+ years). Thus, in Appendix A2 we initially run separate regression for each of the following spells – 3 years, 4, years, 5years, 6 years, 7years, and 7+ years, controlling for initial size and MSA fixed effects. Standard errors are clustered by MSA. This table therefore presents results from 36 regressions (6 skill descriptors x 6 periods). We find the initial score on each of the six skill variables predicts the skills scores of establishments 3 to 7+ years into the future. These effects are both statistically and economically significant. For instance, a one standard deviation increase in the initial rank on complex problem solving increases the future percentile rank of complex problem solving skill by 12-19 percentile ranks in the next 7 years. We find similar significant results with the scores on the other skills. Five years from the time the entrant first appears in the data, a one standard deviation in the initial rank increases the future rank by 13.82, 10.71, 21.13, 14.43, 15.27 and 14.64 percentile ranks for COMPLEXPS, NRCOG, INTERCOMP, RMAN, OFFSH, and COMPPROB respectively. In unreported statistics, we get similar evidence of persistence when we look at the large sample of incumbent firms.

Overall, Table 3 provides evidence that the founding skill profile of an establishment has a strong persistence effect and predicts the future skill profile of the establishment during the early life-cycle of the firm. Thus, a decline in the quality of entrants is likely to have a persistent effect that affects the niche in its industry that the firm can profitably occupy.

D. Growth and Initial Skill

In this section we explore if the initial skill impacts the growth trajectory of the establishment by estimating the following set of equations. For firm *i* in industry *j*:

$$\Delta Employment_{Entrant,jt} = \mu + \beta_1 Initial\ Skill_{i0} + \beta_2 Initial\ Size_{i0} + \beta_3 Age + \delta_j + \pi_{MSA} + \gamma_t + \upsilon_{it} \quad (2)$$

We estimate an analogous specification for incumbent firms. In (2), the dependent variable is the annual growth rate of all entrant firms that entered in our sample period followed to the end of our sample period. For incumbents, the dependent variable is the annual growth rate of the incumbent firms that entered in our OES sample period when they were age 3 and older followed till the end of our sample period. Initial Size and Initial Skill are measured the first time the incumbent appears in the dataset.

We restrict both sets of regressions to firms with more than 5 employees given our discussion in section II.C. All regressions include year fixed effects, 4-digit NAICS fixed effects and MSA fixed effects and are clustered by firm. For the incumbent sample, as robustness we also use MSA x Year and NAICS4 x Year fixed effects which is not possible in equation (5) due to the smaller sample size.

Panel A of Table 4 presents regression estimates for the entrant sample whereas panel B of Table 4 present regression estimates for the incumbent sample. In columns 1-6 when we don't include industry fixed effects we see that a high initial rank on COMPLEXPS, NRCOG, and INTERCOMP is positively associated with firm growth. Columns 7-12 of Panel A of Table 4 show that initial skill rank is not very significantly associated with firm growth when we include 4-digit NAICS fixed effects. We only see that a high offshorability rank is negatively associated with firm growth. Overall, these results suggest that more skilled entrants grow faster, but that much of that differential can be explained by the faster average growth of entrants in industries chosen by highly skilled entrants.

Panel B of Table 4 presents regressions estimates for the incumbent sample where initial skill rank is the initial percentile skill rank the first time the incumbent appears in the database. Columns1-6 of Panel B show that when we don't include industry fixed effects, a high initial rank on COMPLEXPS, NRCOG, and INTERCOMP is positively associated with firm growth whereas a high initial rank on RMAN, and OFFSH is negatively associated with firm growth. Columns 7-12 of Panel B show that even when we include 4-digit NAICS fixed effects, we find that a high initial rank of COMPLEXPS, NRCOG, and INTERCOMP is still positively associated with firm growth.

In Appendix Table A3, we explore if there is non-linearity in the relationship between initial skill and firm growth by creating 4 dummies which take value 1 if the initial skill rank is ≤10, between 11 and 50, 51-90, and above 90 correspondingly and 0 otherwise. In columns 1-6 of panel A when we don't include 4 digit NAICS fixed effects, we see that higher skill ranks of entrants are associated with higher growth for COMPLEXPS, NRCOG, and INTERCOMP while a very high skill rank above 90 on OFFSH is associated with lower growth. In the presence of 4-digit NAICS fixed effects in columns 7-12, we see that when the initial COMPLEXPS skill rank is above 10 there is a strong positive association between skill rank and growth but we don't get much significance with the other skill measures.

In panel B, we examine if there is non-linearity in the relationship between initial skill and firm growth for the incumbent sample. We see that COMPLEXPS, NRCOG, and INTERCOMP skill ranks above 10 are positive and significantly associated with firm growth whereas very high RMAN and OFFSH skill rank (above 90th percentile) are negatively associated with firm growth. These are robust to including industry fixed effects. When we don't include industry fixed effects, COMPPROB between 11 and 90 is negatively associated with firm growth.

In Appendix Table A4 we look at the relationship between initial skill and exit. Exit is identified in the QCEW sample by the date of last positive employment. Exit dummy takes the value 1 in the year of exit and 0 otherwise. We run logit estimations controlling for year and MSA fixed effects in the full sample as well as across industry sub-samples. Industries that are below median skill value in 2005 are defined as Low Skill and those that are at median or above skill value in 2005 are defined as high skill industries. The table shows some evidence that high skilled incumbents are less likely to exit than low skilled incumbents. When we look across industry-sub-samples, we have some evidence that high skilled entrants are less likely to exit than low skilled entrants in low skilled industries. There is not much difference in the probability of exit of incumbents across low skilled and high skilled industries. We do not rely on these results too much as the exit here could reflect a successful exit wherein the establishment is taken over by a larger firm.

Overall, we see strong evidence that initial skill is predictive of future growth. This suggests that the consequences of the decline in entrepreneurial quality may be more severe in in the long run.

IV. Import Competition Skill and Growth in US Manufacturing

W next examine the impact of increased competition using trade shocks. The international trade literature has established that trade shocks measured by import tariffs drive quality upgrading (e.g. Amiti and Khandelwal, 2013) and more generally productivity (e.g. Pavcnik, 2002; Amiti and Konings, 2007; Topalova and Khandelwal, 2011). Given the importance of globalization, and in particular, manufacturing imports from China, on U.S. manufacturing industries, we investigate whether Chinese import penetration predicts changes in skill levels and growth patterns of U.S. entrants and incumbents. More broadly, competition from Chinese imports represents an easily measurable component of product competition and thus stands in for any similar competitive shocks.

We first estimate the following specification to study the impact of trade shocks on skill:

$$Skill_{ijt} = \mu + \beta_1 Entrant_i + \beta_2 Imports_j^{US} + \beta_3 Imports_j^{US}\ x\ Entrant_i + \beta_4 Initial\ Size_{i0} + \beta_5 Entrant_i \times \gamma_t + \delta_j + \pi_{MSA} + \upsilon_{ij} \quad (3)$$

where the dependent variable $Skill_{ijt}$ is the skill score of establishment *i* and could be of one of the following: COMPLEXPS, NRCOG, INTERCOMP, RMAN, OFFSH, and COMPPROB; μ is the average response across all firms; Initial Size is defined when the firm first appears in the database for incumbents and at age 0 for entrants; Entrant is a dummy variable to distinguish between entrants and incumbents; $Imports_j^{US}$ is the instrumented value of annual Chinese import exposure faced by US industries; δ_j are 4-digit NAICS fixed effects, and π_{MSA} are MSA fixed effects, and the υ_{ijt} are random disturbances. Our main variable of interest in the regressions is β_3, the differential impact of the instrumented value of Chinese import exposure faced by US industries on entrants versus incumbents.

To examine the impact of trade shock and initial skill on growth we estimate the following:

$$\Delta Employment_{Entrant,jt} =$$

$$\mu + \beta_1 Initial\ Skill_{i0} + \beta_2 \Delta Imports_{jt}^{US} + \beta_3 Initial\ Skill_{i0}\ x\ \Delta Imports_{jt}^{US} + \beta_4 Initial\ Size_{i0} + \beta_5 Age +$$

$$\delta_j + \pi_{MSA} + \gamma_t + \upsilon_{it} \qquad (4)$$

where ΔImports is the annual change in Chinese import exposure in each 4-digit NAICS industry (instrumented) as defined in the Web Appendix . We estimate an analogous specification for Incumbent growth.

Panel A of Table 5 presents the results from estimating (3). Panel A shows that in industries facing high import exposure, entrants have lower COMPLEXPS, NRCOG AND INTERCOMP skills than incumbents. Entrants also seem to have higher routine manual skills and offshorability than incumbents in industries exposed to Chinese import competition. We also see that entrants are less likely to have high offshorability scores in industries with high import shocks.

In Figure 9 we present the economic effects of the regression in cols. 1-4 of Panel A of Table 5. We compare the difference in skill scores for entrants and incumbents in 2005, 2008, and 2011 for the realized value of imports with what these differences might have been if the imports were lower than the realized value. Given the realized value of imports, entrant

COMPLEXPS scores are higher than that of incumbent scores in 2005 but by 2011, entrant scores are lower than that of incumbent scores, a decline which is 23.9% of the standard deviation in COMPLEXPS.[18] Similarly the difference between entrants and incumbents over the period 2005 and 2011 for the other skills are as follows: there is a decline of 12.7% of standard deviation in NRCOG, decline of 31.3% of standard deviation of INTERCOMP and an increase of 18% of standard deviation of RMAN.[19]

Looking across the cross-section in 2011, if the imports were cut to 1% of their actual value, the difference in COMPLEXPS between entrants and incumbents would decrease by 41%.[20] Similarly in 2011, the differential between entrants and incumbents in NRCOG, INTERCOMP, and RMAN skills would be cut by 60%, 17% and 26% respectively if the imports were 1% of their actual value. Overall while Chinese imports contribute to the decline in skills over time from 2005 to 2011, the evidence suggests a persistent decline in skill even if Chinese imports were only 1% of their realized value. Taking these estimates as upper bounds suggests that even a total cessation in imports would only have cut the differential in 2011 between entrants and incumbent firms and entrants in US manufacturing between 17 to 60%.

In Panels B and C of Table 5, we take a closer look at entrants and incumbents separately. Panel B shows that in industries with high Chinese import shocks, entrants have lower interactions with computers, higher routine manual and lower offshorability skills. Panel C shows that in industries with high Chinese import shocks, incumbents have higher complex

[18] =(-0.087-0.019)/0.448

[19] These declines would be 16% of SD in case of COMPLEXPS if imports were 1% of realized value in 2011, 4% of SD in NRCOG, 25.5% in case of INTERCOMP and 10.9% in case of RMAN.

[20] In 2011, the difference in COMPLEXPS between entrants and incumbents with actual value of imports is -0.088 and with 1% of actual imports this difference is -0.052. % decrease =-0.052+0.088)/-0.088=-41%. In other words, 59% of the difference in COMPLEXPS between entrants and incumbents would still exist if imports were to be only 1% of actual value.

problem solving, non-routine cognitive analytical skills, and interactions with computers, and lower routine manual and offshorability skills. Overall, this suggests that incumbent manufacturing firms upgrade their skills in response to Chinese import competition whereas manufacturing entrants' are differentially exposed to Chinese import competition and come in less skilled.

In Table 6, we estimate the same regressions for industries that are below median skill value in 2005 (Low Skill) and those that are at median or above skill value in 2005. Table 6 shows that the skill differential between entrants and incumbents in response to Chinese import competition is most pronounced in low skill industries. We do not see any difference in COMPLEXPS, NRCOG, and INTERCOMP in high skill industries. We do see that in high skill industries, entrants are performing more routine manual tasks than incumbents in response to Chinese import competition whereas this effect does not exist in low skill industries. We find materially similar results if we were to split industries into low-tech and high-tech industries based on the classification in Goldschlag and Miranda (2016).

In Table 7, we examine the interaction of initial skill and annual changes in Chinese shock on subsequent firm growth for entrants in Panel A and incumbents in Panel B. In Panel A controlling for year, MSA, and NAICS4 fixed effects, we find that establishments with high initial complex problem solving and non-routine cognitive skills grow faster in industries facing high growth in Chinese imports. In Panel B we repeat the above specification for incumbents and see that the interaction of Initial Skill and Changes in Chinese Import shock is positive and significant for COMPLEXPS, NRCOG, and INTERCOMP suggesting that in industries with high competitive trade shocks, high skilled incumbents grow faster. In column 5 of panel B, we also see that incumbents with high scores on OFFSH grow less fast when faced with high trade shocks.[21] In unreported statistics we find similar results controlling for MSA x Year and NAICS fixed effects.

The 2008 global financial crisis occurs right in the middle of our sample period. While we include year fixed effects in all our regressions to control for the effects of the crisis, to address concerns on the crisis effects affecting the interpretation of our results, we split our sample into three periods: pre-crisis (2005-2007), crisis period (2007-2010), and post-crisis (2010-2013). All the regressions include MSA, Year, and NAICS4 fixed effects as before.

Panel A of Table 8 present results for entrants and panel B present results for incumbents. For the entrant sample we find some evidence that entrants with high initial skills in industries exposed to Chinese import shocks grow faster during the crisis period. In panel B, we see significant effects of initial skill on the growth of establishments in industries exposed to trade shocks for incumbents. In industries with high Chinese imports, incumbents with high scores on COMPLEXPS and NRCOG grow faster during the crisis period and the period after the crisis. We also see that incumbents with high scores on OFFSH grow less fast in the industries facing high Chinese import competition during the crisis period and the period after the crisis.

Overall, there is a competitive upgrading of the human capital of incumbents in industries exposed to large competitive shocks whereas entrants come in less skilled in these industries. Competitive shocks cause more skilled firms to grow relatively faster, for both incumbents and entrants).

[21]Adelino, Ma, and Robinson (2017) in their study on non-tradeable sectors find entrants to be more responsive to demand shocks than incumbent firms. Here our focus is on how entrants with different skill levels react to a competitive shock, and separately, how incumbents with different skill levels react to the same shock.

V. Discussion

In this section we consider alternate theories for the decline in skill level of entrepreneurial firms.

First in unreported statistics we confirm that there is an independent effect of Chinese imports and initial skill on establishment growth from initial industry conditions (in 2005). In a regression of establishment growth on initial skill, Chinese imports, and initial industry skill, we see that each of these have independent effects on establishment growth.

Next, to understand whether the decline in skill level of new firms is due to technological changes that might affect the skill mixes of de novo and incumbent establishments, we compare the single establishments entrants (entrepreneurs) with the new plants of multi-establishment firms. If it were technological changes that were causing changes in skill of the entrants, we would expect to see new plants of existing multi establishment firms to also show similar changes in skill. We begin by repeating the estimation in Table 2 but for entrants and incumbents of multi-establishment firms. Figure 10 plots the predictive margins of the interaction of entrant dummy and year. We see that incumbent and entrants of multi-establishment firms do not look different in their skill profiles. Next we compare entrants of single establishment firms with entrants of multi establishment firms, that is, new plants. Figure 11 plots the predictive margins of the interaction terms and shows that new plants of multi establishment firms do not show the same decline in skill as the new entrants of single establishment firms. Thus the skill level of new entrepreneurs has declined compared to all other establishments.

In Table 9, we repeat the specification in Table 5 but this time comparing entrants with new plants (entrants of multi-establishment firms). Due to the small sample of entrants and new plants we are unable to control for industry fixed effects in these regressions. Table 9 provides some evidence that in industries facing high import exposure, new plants upgrade their COMPLEXPS skills compared to entrants. Entrants also seem to have higher offhsorability and computerization probability compared to new plants in industries exposed to Chinese import competition.

An alternate explanation for these results could be that since 2005, the nature of innovation has changed and it has become easier to split innovation from manufacturing and thus entrants first start off as non-manufacturing and eventually switch to manufacturing. When we analyze the entrants who switched within two years of entry from non-manufacturing into manufacturing, we do see that they tend to be of higher average skill than entrants who directly entered manufacturing. This sub-sample, about 20% of all entrants, does not exhibit the same decline in skills over our period.

Finally, we explore how results are reflected by changes happening within the entrant firms in the distribution of high skill vs low skill employees. Figure 12 shows that within the entrant firms, the proportion of workers in occupations requiring low complex problem solving skills is increasing, whereas the proportion in occupations requiring high complex problem solving is declining. The proportion of workers in occupations requiring mid-level skills is relatively stable. Thus, in the entrant sample we do not see job polarization as much as the replacement of highly skilled workers by less skilled occupations.

VI. Conclusion

Recent academic and policy debate has focused on the declining rate of entrepreneurship in the overall US economy, even as US firms are facing increasing competitive pressures from globalization. We show that over the 2005-2013 period there is a decline not only in the number of new businesses in US manufacturing, but also in their size and quality, measured by the tasks which their workforce performs.

This has significant long-term consequences because we show that the founding stock of human capital in entrants is predictive of their future human capital as well as growth rates over the early life cycle. Thus, the lower quality and smaller size of the entrants is likely to be perpetuated over time.

The data on incumbent manufacturing firms provides a counterpoint for the experiences of the entrants. As in the case of the entrants, prior levels of human capital predict subsequent levels of human capital, and future growth. However, in contrast to the entrants, manufacturing incumbents show no evidence of declining levels of human capital over time.

The contrast between entrants and incumbents is most stark in their reactions to a competitive threat from Chinese imports. While incumbent firms upgrade their human capital in response to increased competition, the quality of the entrants is minimally affected. As the level of imports increases, more skilled incumbents grow faster than incumbents with lower skills. Overall, these competitive effects on skills are economically are significant. Imports contribute to 12.7% to 31.3% of the standard deviation decline in average entrant skills relative to that of incumbents over the period 2005-2013. However, even a total cessation in imports would only have cut the differential in 2011 between entrants and incumbent firms and entrants in US manufacturing between 17 to 60%.

The decline in entrepreneurial quality in manufacturing is real but is only partially responsive to the level of Chinese imports. It is more consistent with technological polarization, whereby incumbent firms upgrade their human capital, and entrepreneurial firms are finding investment opportunities in niches employing less skilled labor. This polarization is particularly stark in industries facing import competition where incumbents are upgrading their human capital most, both in their legacy plants and in the new plants they construct.

These developments echo the findings of the labor literature that there has been a trend for the polarization of jobs, with increases in high and low-skilled jobs, and a contraction of jobs in the middle. Our results, suggests an additional polarization in which high and low skilled workers will be working in different firms. Entrepreneurial manufacturing firms may take on low-skilled tasks that can be offshored or outsourced by incumbents, and that will eventually be automated.

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Figure 1: Import Penetration Ratio

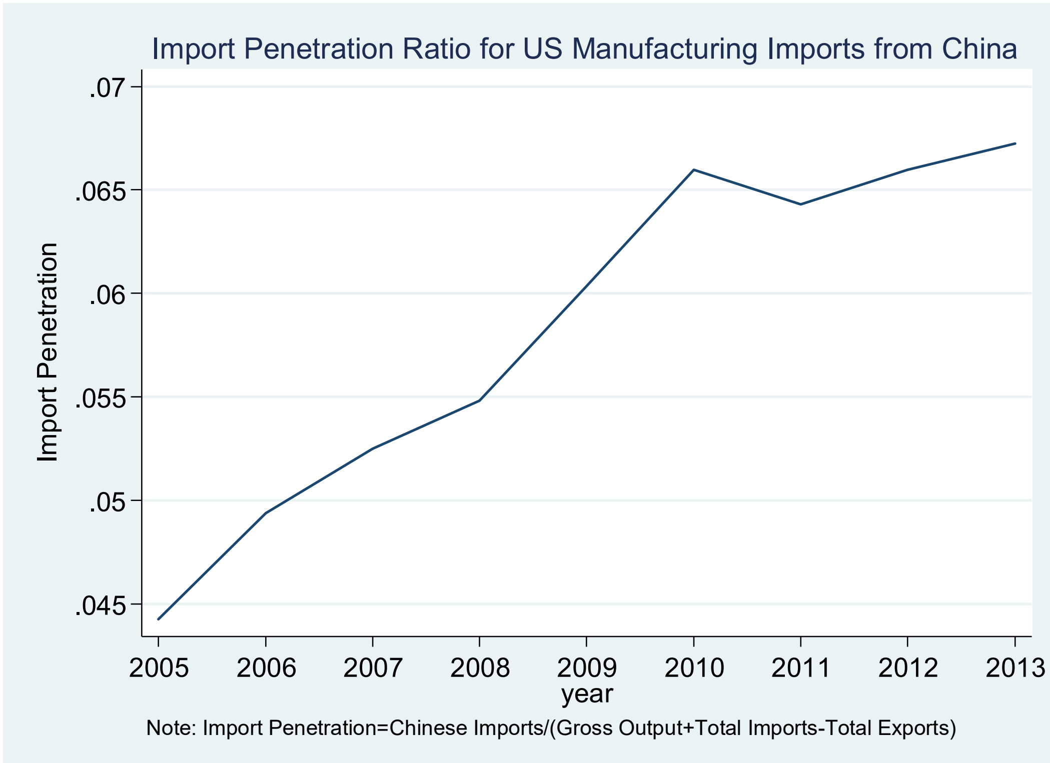


Figure 2: Entry Rates in Manufacturing

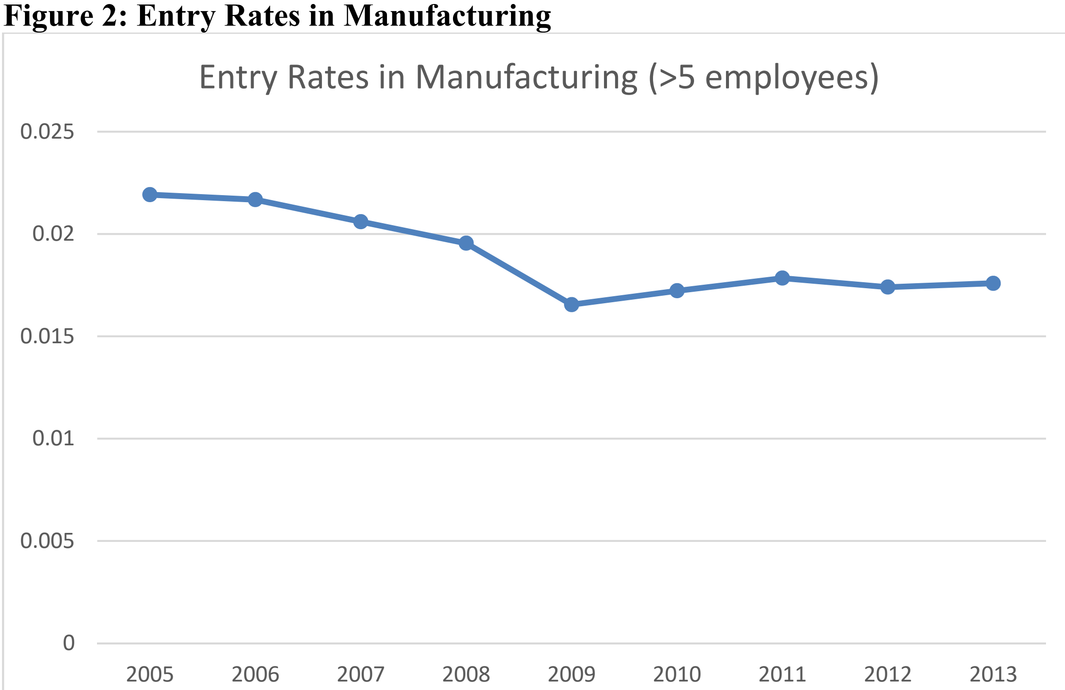


Figure 3: Entry Rates in Manufacturing Industries that faced low versus high imports over the period 2005-2013

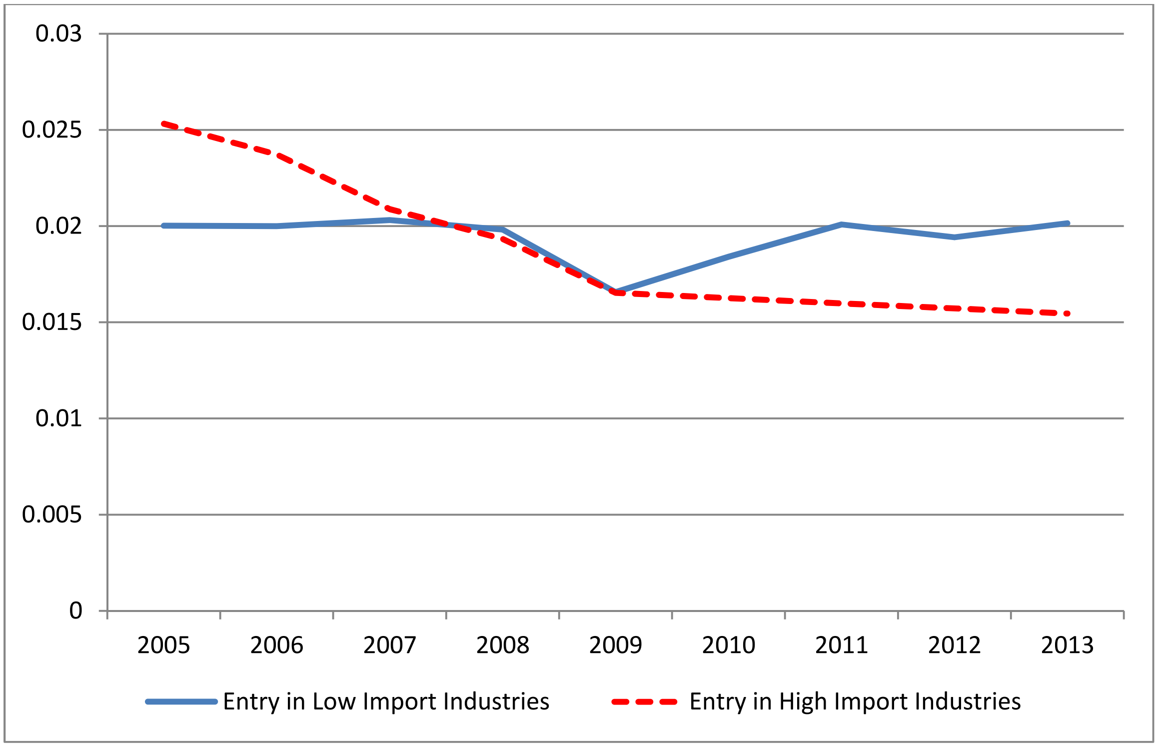
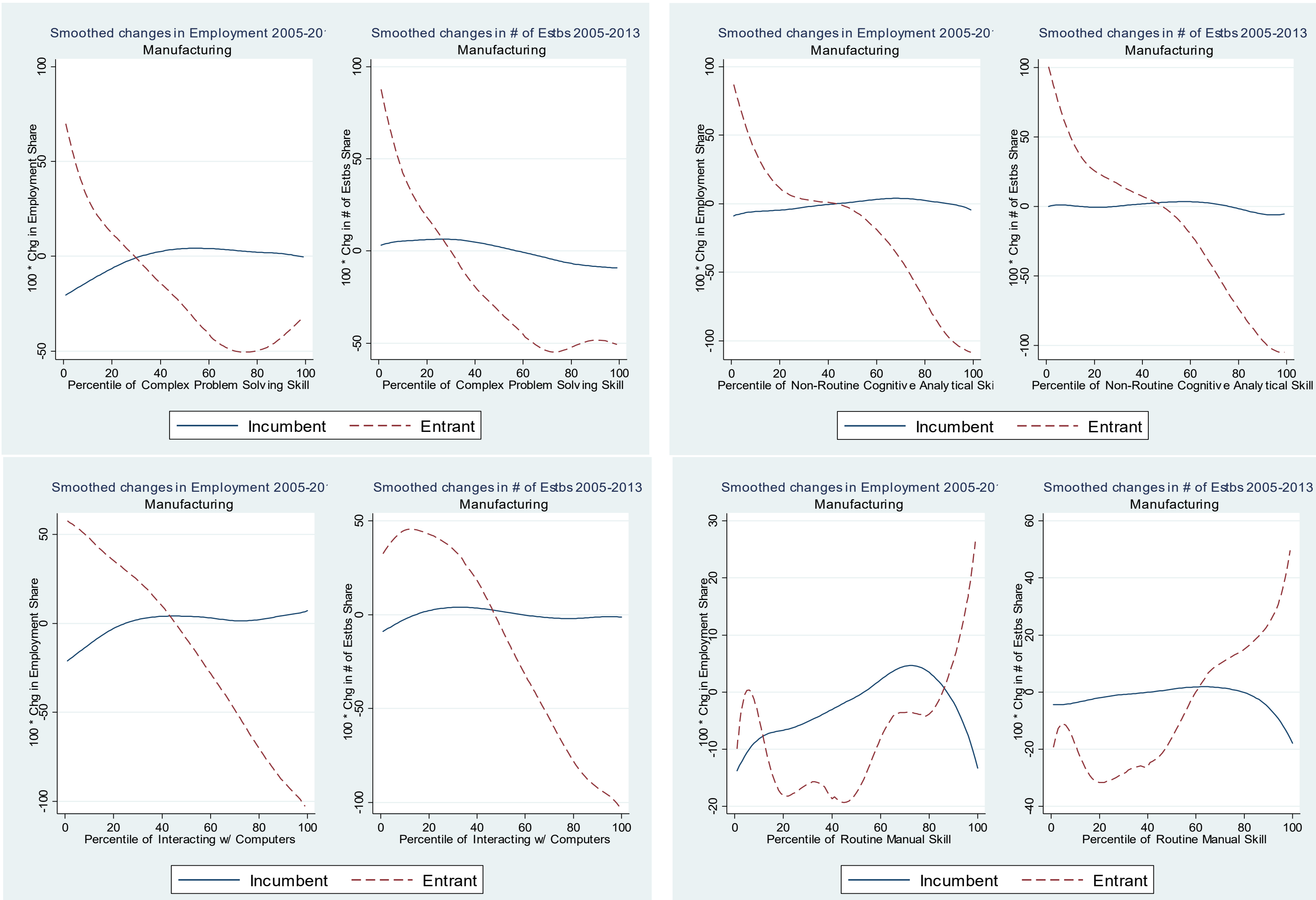
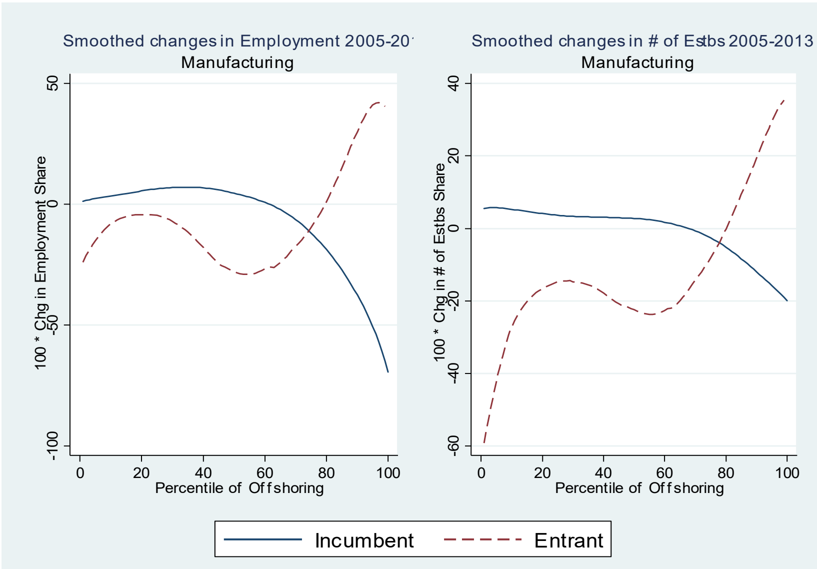


Figure 4: Changes in Employment Share and Establishment Share across Skill Distribution




Smoothed changes in Employment 2005-20
Manufacturing
100 * Chg in Employment Share
Percentile of Offshoring
Smoothed changes in # of Estbs 2005-2013
Manufacturing
100 * Chg in # of Estbs Share
Percentile of Offshoring
Incumbent
Entrant

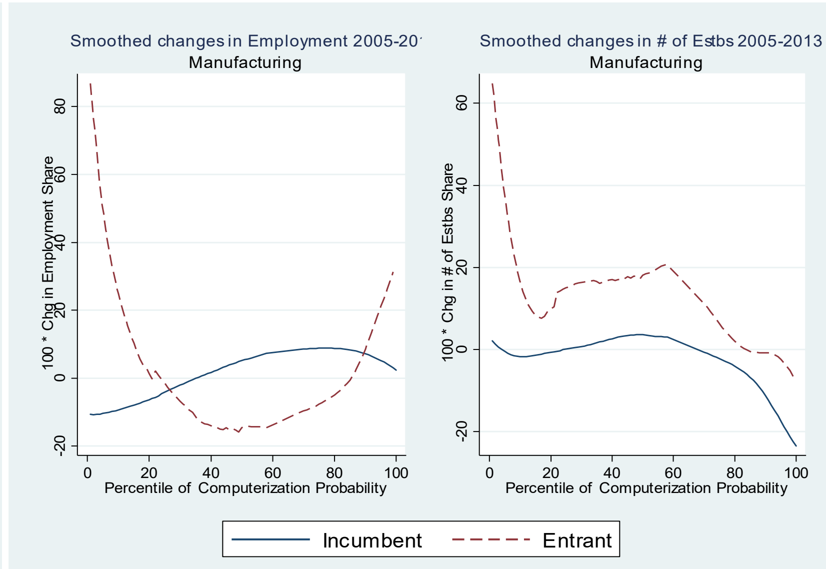
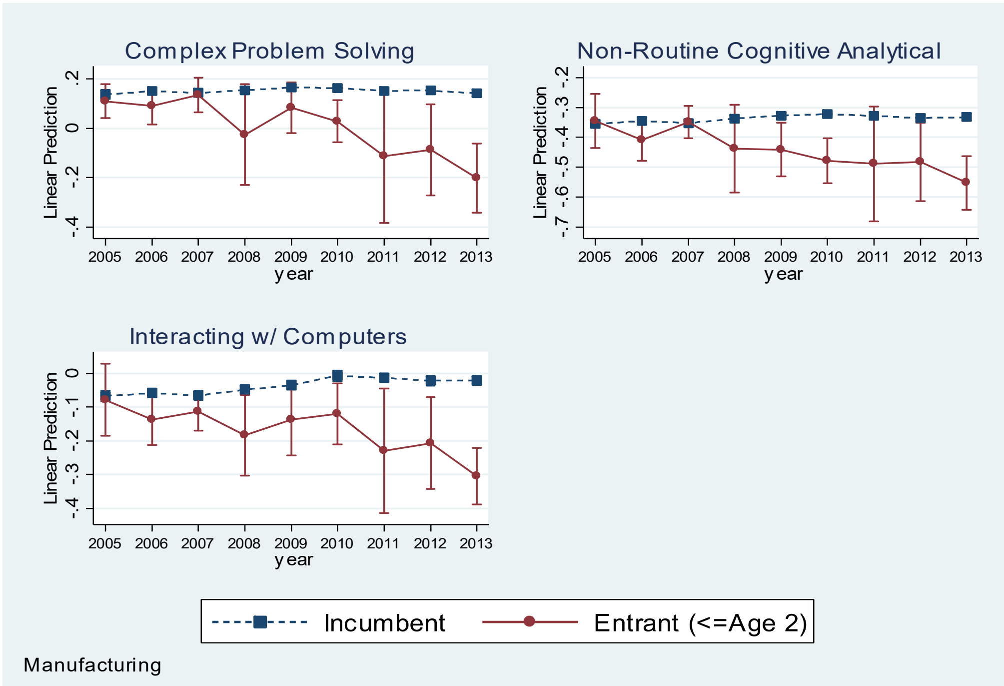

Smoothed changes in Employment 2005-20
Manufacturing
100 * Chg in Employment Share
Percentile of Computerization Probability
Smoothed changes in # of Estbs 2005-2013
Manufacturing
100 * Chg in # of Estbs Share
Percentile of Computerization Probability
Incumbent
Entrant

Figure 5: Skills of Entrants vs Incumbents in Manufacturing-Predictive Margins of panel A of Table 2



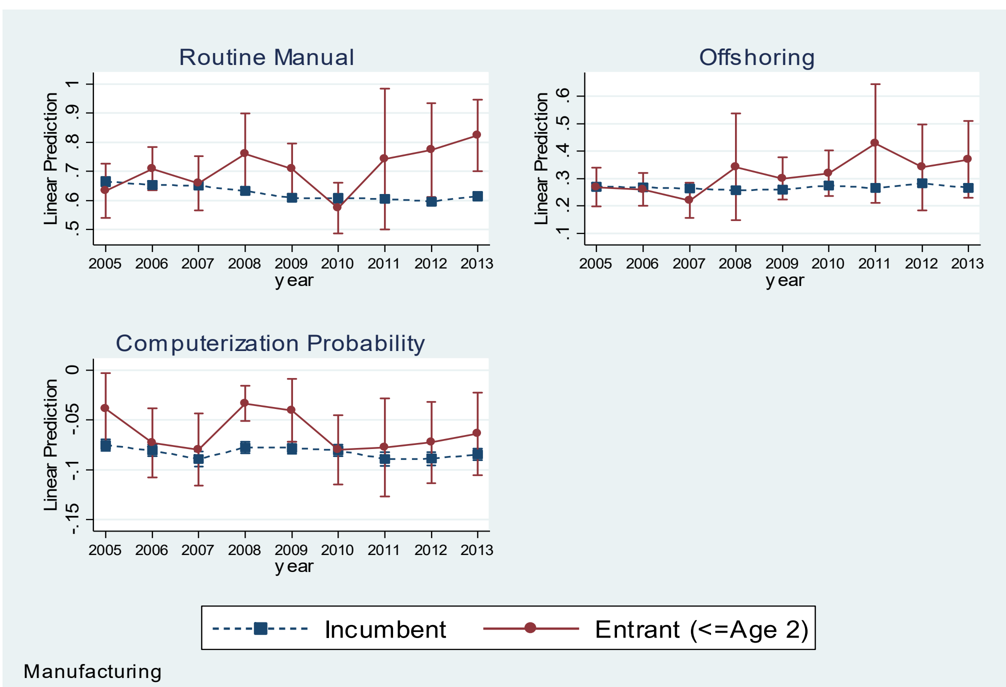
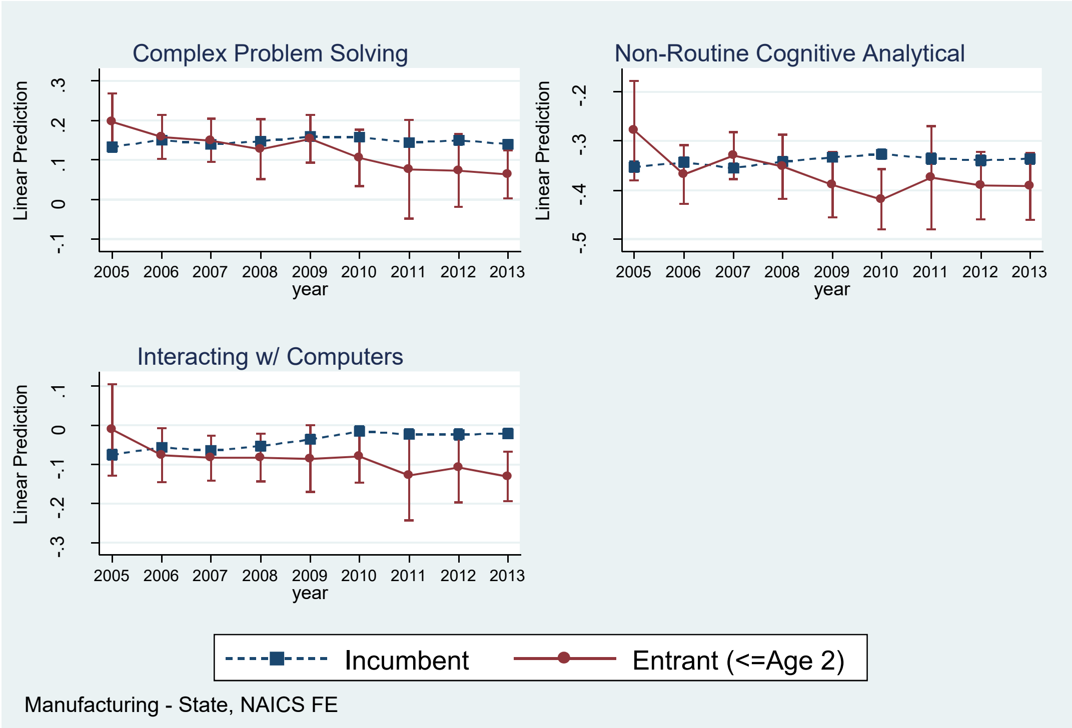


Figure 6: Skills of Entrants vs Incumbents in Manufacturing-Predictive Margins of panel B of Table 2



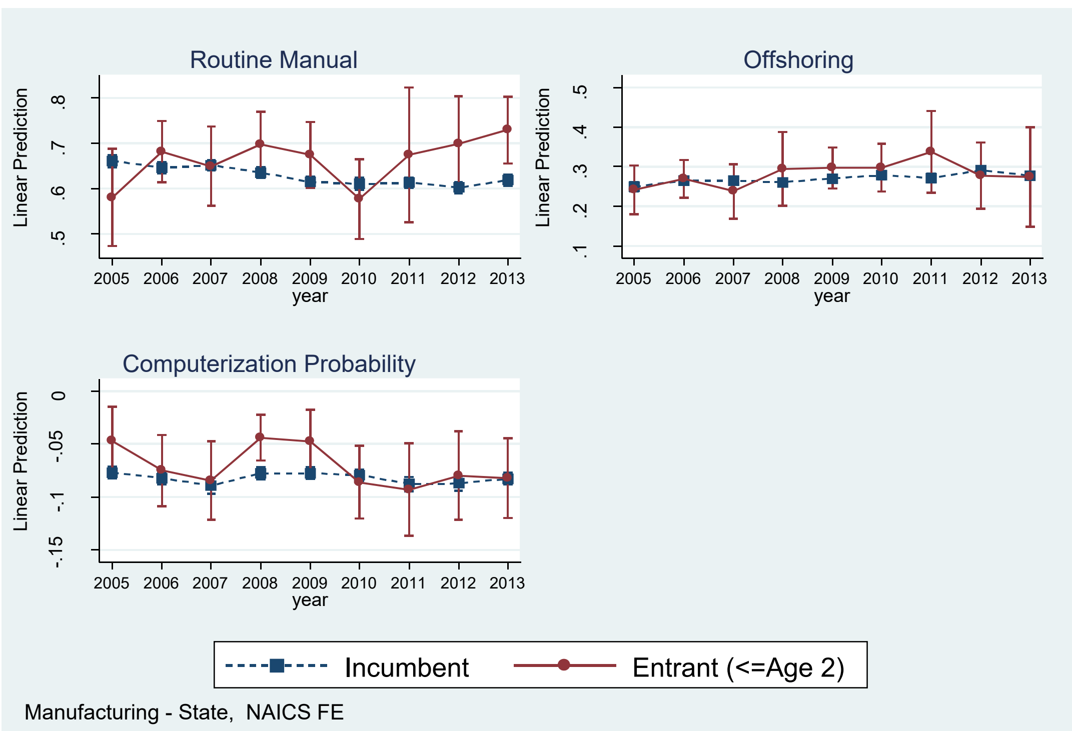


Figure 7: Scatter Plot between initial complex problem solving skill and future complex problem solving skill

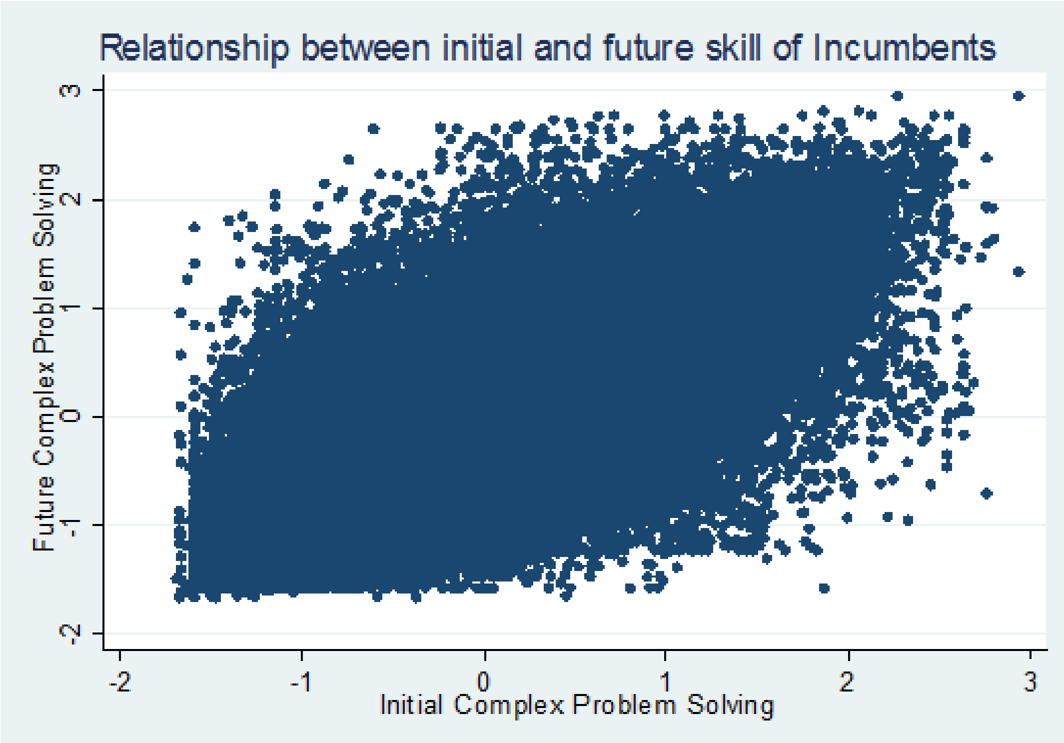


Figure 8: Association between Initial and Future Skill Rank

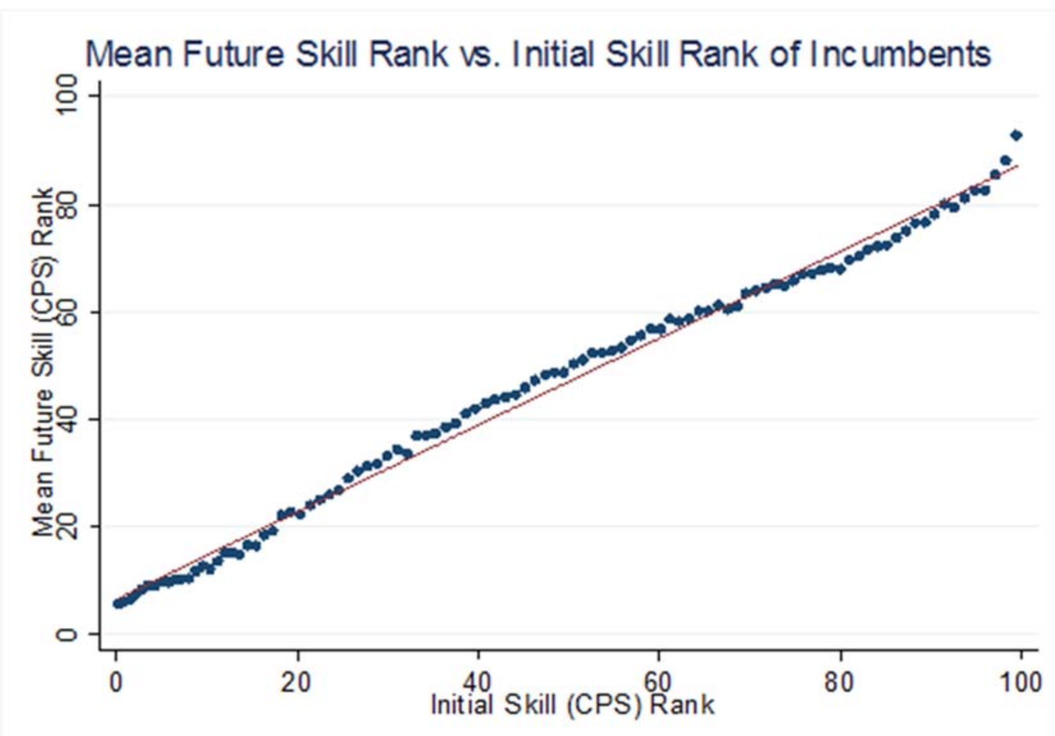


Figure 9: Economic Effects of Regression in Panel A of Table 5

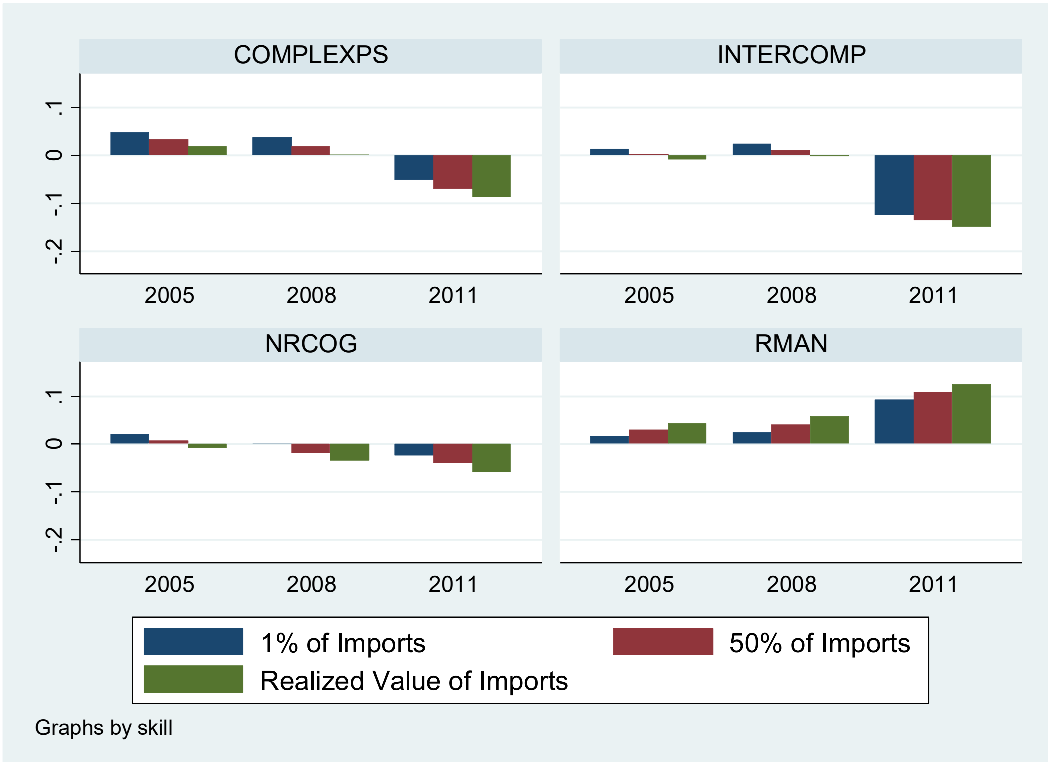
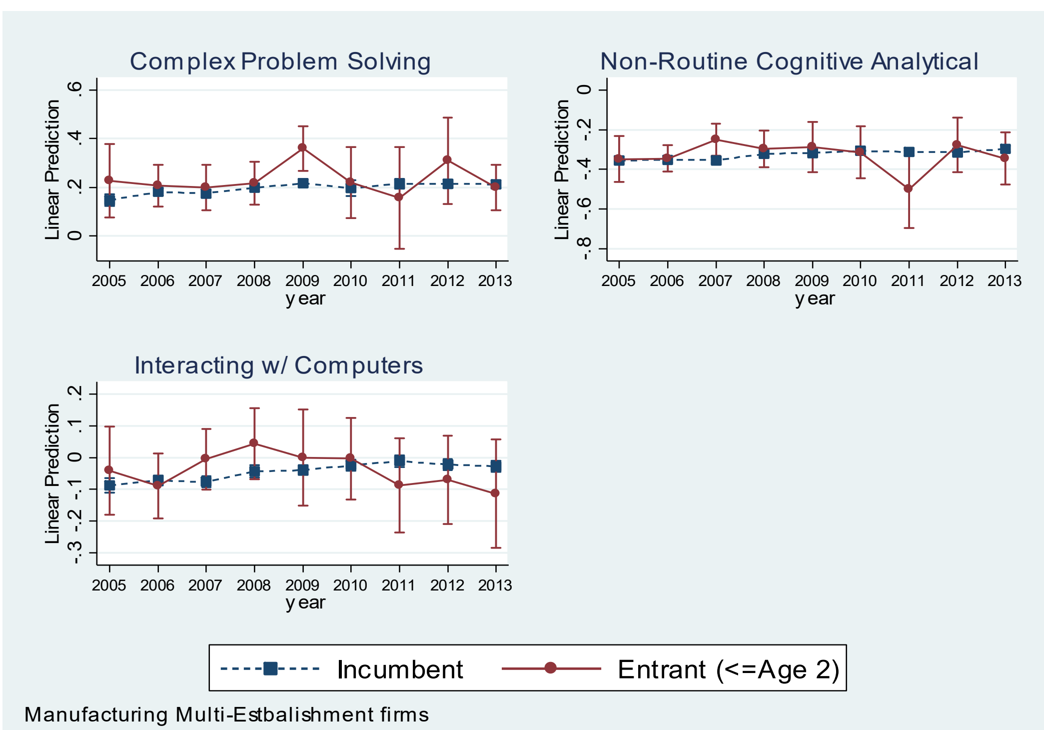


Figure 10: Entrants vs Incumbents of Multi Establishment Firms



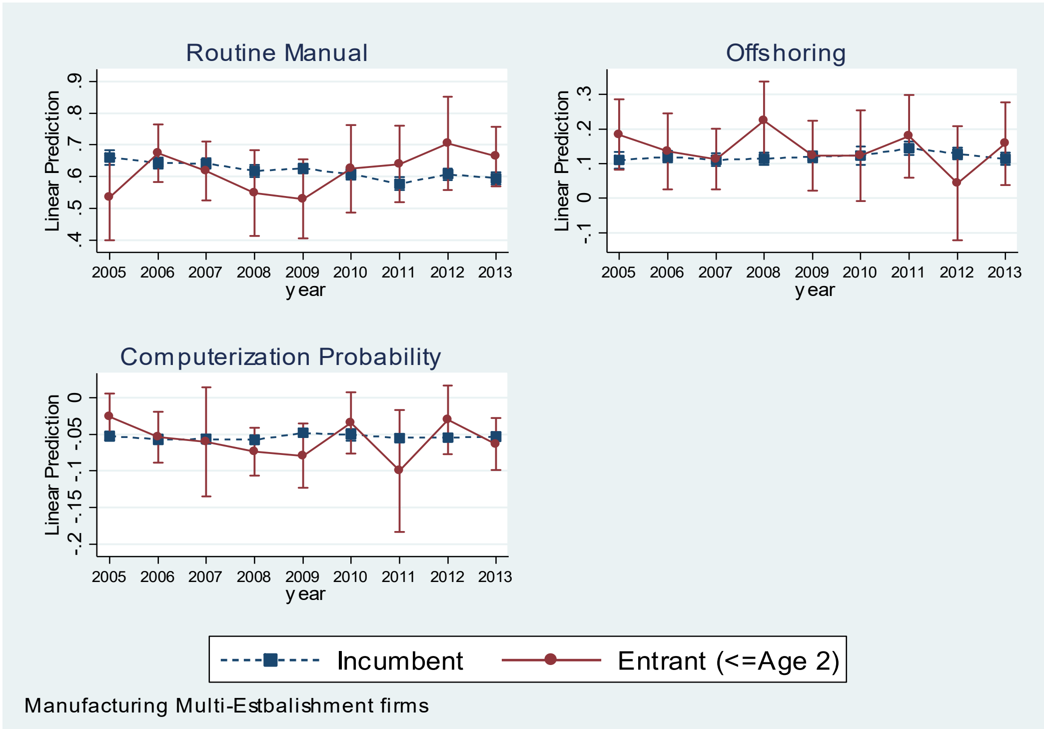
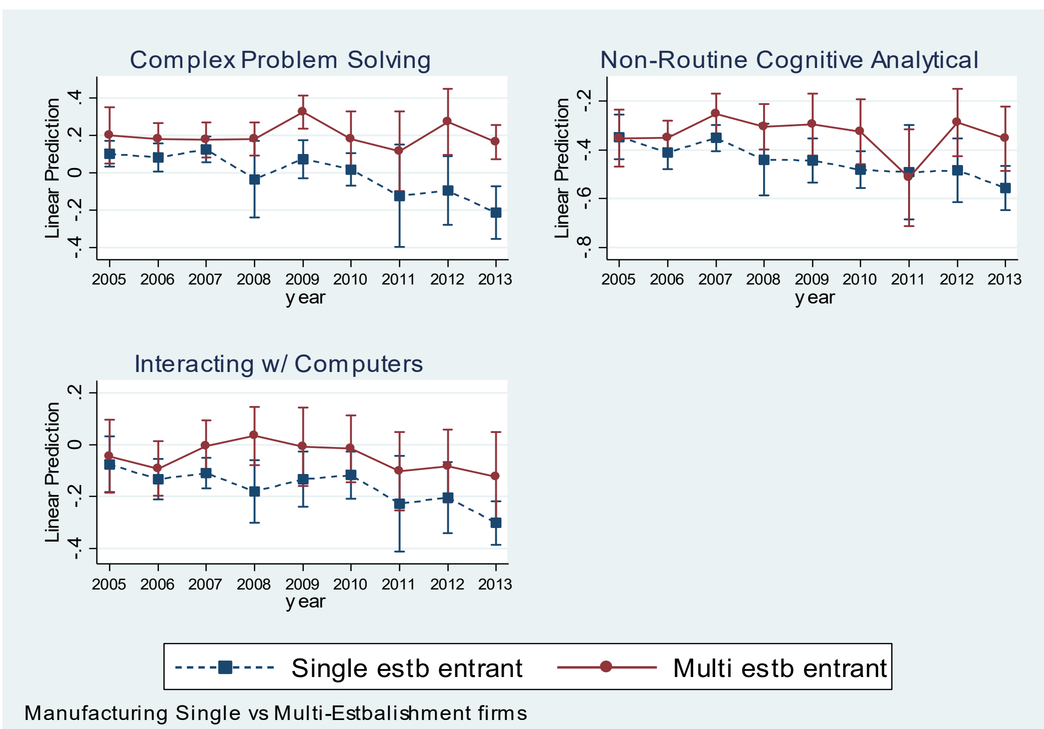


Figure 11: Entrants of Single Establishment Firms vs New Plants



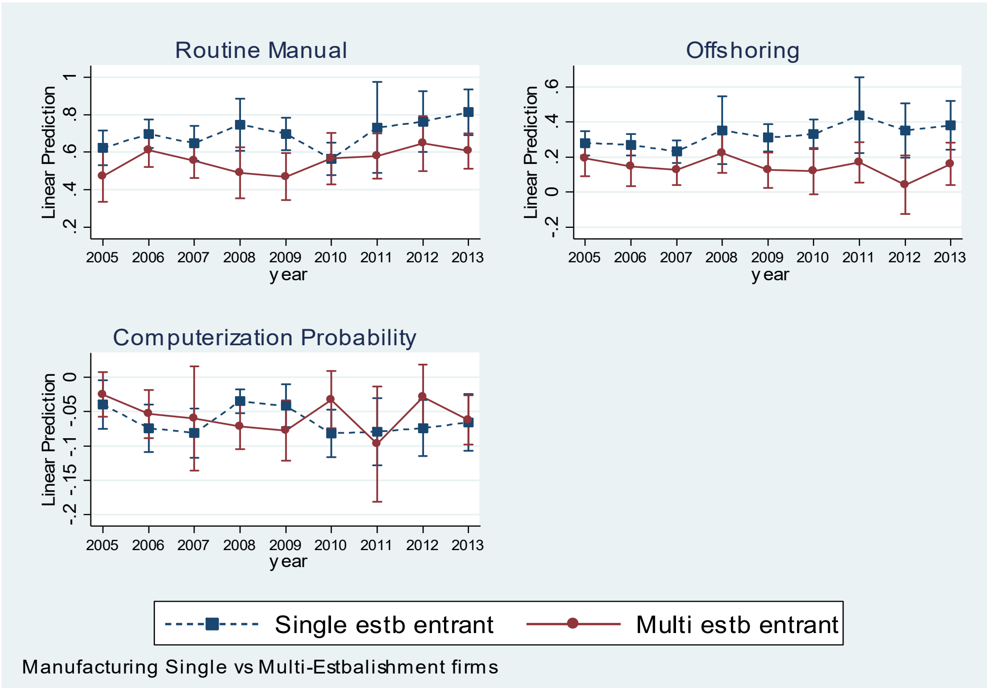


Figure 12: Within the firm

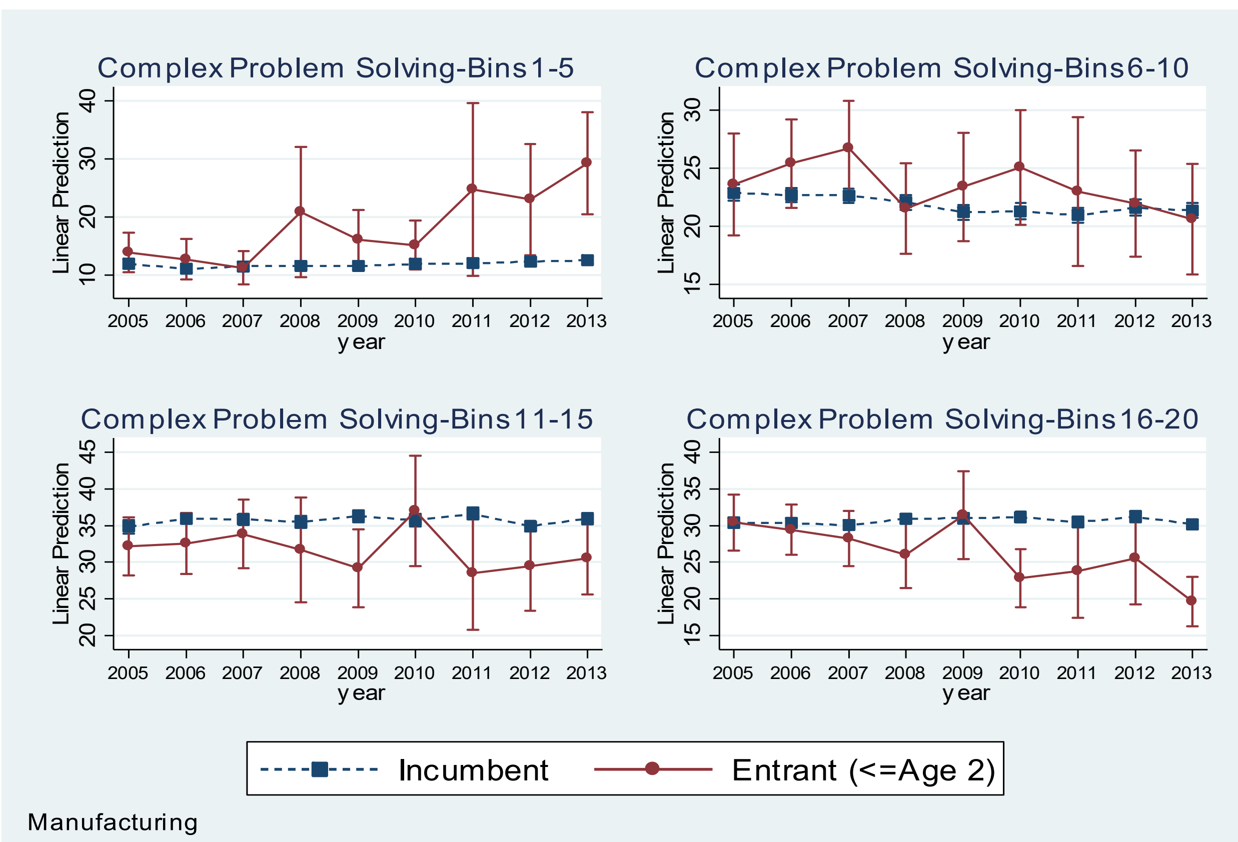


Table 1: Entry Rates

Panel A of this table shows the entry rates across major industry groups over 2005-2013. Panel B breaks down the entry rates in manufacturing by employee size class. Entry rate is defined as the number of establishments less than 1 year old in that industry/Total number of establishments in that industry x 100. The last row shows the percentage change in entry rates over the entire period. Source: Business Employment Dynamics

Panel A: Across Major Industries

Year	**All Private**	**Manufacturing (NAICS 31-33)**	**Natural Resources & Mining (NAICS 11)**	**Construction (NAICS 23)**	**Wholesale & Retail Trade (NAICS 42-45)**	**Transport & Warehousing (NAICS 48-49)**	**Services (NAICS 51-56, 61-62. 71-72)**
2005	25.55	5.44	17.22	26.16	22.35	25.25	26.21
2006	25.72	5.40	17.67	26.20	22.29	26.50	26.23
2007	25.65	5.52	18.13	26.34	22.13	26.44	26.15
2008	25.46	5.42	18.34	25.12	21.90	25.92	26.55
2009	26.47	4.71	19.14	24.43	23.09	26.91	27.42
2010	24.27	4.40	17.97	20.44	20.31	23.53	25.93
2011	22.51	4.77	17.20	18.65	19.20	23.18	24.61
2012	23.17	5.12	17.95	18.95	19.38	24.45	25.12
2013	23.38	5.14	19.28	19.33	19.32	23.26	24.88
Δ	*-8.53*	*-5.45*	*11.93*	*-26.08*	*-13.58*	*-7.90*	*-5.06*

Panel B: Entry Rates in Manufacturing by Size Class

		Number of Employees						
	All sizes	**1-4**	**5-9**	**10-19**	**20-49**	**50-99**	**100-499**	**500+**
2005	5.44	4.32	0.62	0.30	0.16		0.01	
2006	5.40	4.37	0.58	0.28	0.14	0.03	0.01	0.00
2007	5.52	4.49	0.59	0.28	0.13	0.02	0.01	0.00
2008	5.42	4.47	0.57	0.25	0.11	0.02		
2009	4.71	3.94	0.48	0.18	0.09	0.01		0.00
2010	4.40	3.65	0.45	0.20	0.08	0.01	0.00	0.00
2011	4.77	4.05	0.44	0.18	0.08	0.01		0.00
2012	5.12	4.33	0.48	0.20	0.09			0.00
2013	5.14	4.37	0.47	0.19	0.09	0.01	0.00	0.00
Δ	*-5.45*	*1.32*	*-23.14*	*-37.21*	*-42.22*		*-68.72*	

Table 2: Evolution of Skills over Time

The regression equation estimated here is Skill = $a_0+\beta_1$Entrant + β_2Entrant x Year Dummies + β_3 Year Dummies + β_4 Size Class Dummies + β_5 MSA Dummies + β_5 Industry Dummies + ε. Skill is one of 6 different measures of human capital – COMPLEXPS, NRCOG, INTERCOMP, RMAN, OFFSH, COMPPROB that are defined in detail in Appendix A1.Skill is measured for entrants anytime in the first 2 years of age and for incumbents when the establishment first appears in the sample. Size Class dummies consist of 3 dummies for 6-20 employees, 21-100 employees and 101+ employees (omitted category). MSA dummies are Metropolitan Statistical area dummies. Industry dummies are 4-digit NAICS 2007 dummies. Panel A shows estimates without MSA and industry fixed effects whereas Panel B shows estimates with MSA and industry fixed effects. All regressions are weighted by the sampling weights and are estimated using ordinary least squares with standard errors clustered by industry.

Panel A: Without MSA and industry fixed effects

	1	2	3	4	5	6
	COMPLEXPS	NRCOG	INTERCOMP	RMAN	OFFSH	COMPPROB
Entrant	-0.027	0.009	-0.011	-0.031	-0.001	0.037*
	(0.039)	(0.035)	(0.040)	(0.037)	(0.034)	(0.019)
2006	0.013	0.009	0.009	-0.012	-0.002	-0.005
	(0.008)	(0.008)	(0.010)	(0.008)	(0.006)	(0.004)
2007	0.006	0.002	0.002	-0.014*	-0.007	-0.014***
	(0.005)	(0.005)	(0.006)	(0.008)	(0.011)	(0.004)
2008	0.017	0.018	0.019	-0.032**	-0.013	-0.002
	(0.011)	(0.014)	(0.015)	(0.013)	(0.009)	(0.004)
2009	0.027*	0.027**	0.032**	-0.056***	-0.010	-0.003
	(0.014)	(0.010)	(0.013)	(0.013)	(0.013)	(0.008)
2010	0.026**	0.032***	0.060***	-0.057***	0.005	-0.005
	(0.011)	(0.012)	(0.011)	(0.010)	(0.010)	(0.006)
2011	0.015	0.027**	0.054***	-0.059***	-0.005	-0.014**
	(0.013)	(0.013)	(0.015)	(0.012)	(0.011)	(0.006)
2012	0.015	0.019	0.045***	-0.068***	0.012	-0.013**
	(0.016)	(0.016)	(0.009)	(0.013)	(0.010)	(0.005)
2013	0.004	0.022	0.046***	-0.050***	-0.004	-0.009
	(0.011)	(0.013)	(0.013)	(0.014)	(0.010)	(0.006)
6-20 employees	-0.070***	0.002	0.047***	-0.172***	0.126***	-0.023***
	(0.012)	(0.012)	(0.013)	(0.021)	(0.007)	(0.004)
21-100 employees	-0.007	0.017	0.024**	-0.093***	0.056***	-0.021***
	(0.008)	(0.010)	(0.010)	(0.012)	(0.006)	(0.002)
Entrant x 2006	-0.033	-0.073*	-0.067*	0.088	-0.006	-0.029
	(0.047)	(0.041)	(0.037)	(0.053)	(0.053)	(0.023)
Entrant x 2007	0.019	-0.006	-0.036	0.039	-0.042	-0.027
	(0.047)	(0.042)	(0.046)	(0.062)	(0.046)	(0.021)
Entrant x 2008	-0.152	-0.111	-0.124*	0.158*	0.087	0.007
	(0.114)	(0.081)	(0.063)	(0.079)	(0.108)	(0.024)
Entrant x 2009	-0.054	-0.123***	-0.091	0.132**	0.041	0.001
	(0.048)	(0.044)	(0.064)	(0.056)	(0.055)	(0.032)
Entrant x 2010	-0.108*	-0.166***	-0.102**	-0.002	0.046	-0.036

	1	2	3	4	5	6
	COMPLEXPS	NRCOG	INTERCOMP	RMAN	OFFSH	COMPPROB
	(0.059)	(0.051)	(0.049)	(0.056)	(0.048)	(0.027)
Entrant x 2011	-0.238**	-0.170**	-0.206***	0.168	0.164	-0.025
	(0.105)	(0.064)	(0.072)	(0.107)	(0.103)	(0.039)
Entrant x 2012	-0.212*	-0.157**	-0.174**	0.208*	0.060	-0.021
	(0.109)	(0.077)	(0.071)	(0.113)	(0.111)	(0.029)
Entrant x 2013	-0.315***	-0.229***	-0.272***	0.240**	0.105**	-0.016
	(0.095)	(0.045)	(0.055)	(0.097)	(0.048)	(0.032)
Constant	0.183***	-0.361***	-0.104***	0.802***	0.174***	-0.054***
	(0.018)	(0.012)	(0.012)	(0.017)	(0.021)	(0.005)
Fixed Effects	|-------------------------------------None--|					
N	114863	114863	114863	114863	114863	114863
Adj. R-sq	0.010	0.004	0.006	0.014	0.011	0.002

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Panel B: With MSA and industry fixed effects

	1	2	3	4	5	6
	COMPLEXPS	NRCOG	INTERCOMP	RMAN	OFFSH	COMPPROB
Entrant	0.069*	0.084*	0.081	-0.074	-0.009	0.028*
	(0.038)	(0.043)	(0.052)	(0.046)	(0.024)	(0.016)
2006	0.014**	0.007	0.017**	-0.010	0.014**	-0.007*
	(0.007)	(0.006)	(0.006)	(0.008)	(0.006)	(0.004)
2007	0.003	-0.004	0.009	-0.006	0.013*	-0.014***
	(0.006)	(0.005)	(0.006)	(0.008)	(0.007)	(0.005)
2008	0.010	0.009	0.020***	-0.022**	0.010	-0.001
	(0.006)	(0.006)	(0.006)	(0.009)	(0.007)	(0.004)
2009	0.022***	0.015**	0.035***	-0.042***	0.019***	-0.002
	(0.007)	(0.007)	(0.009)	(0.009)	(0.007)	(0.005)
2010	0.019**	0.020***	0.050***	-0.047***	0.026***	-0.005
	(0.008)	(0.006)	(0.007)	(0.008)	(0.007)	(0.005)
2011	0.007	0.014*	0.048***	-0.043***	0.021***	-0.012*
	(0.006)	(0.007)	(0.009)	(0.007)	(0.008)	(0.006)
2012	0.012*	0.010	0.047***	-0.055***	0.038***	-0.012***
	(0.007)	(0.009)	(0.009)	(0.008)	(0.008)	(0.004)
2013	0.003	0.013*	0.049***	-0.039***	0.024***	-0.009**
	(0.006)	(0.008)	(0.007)	(0.011)	(0.007)	(0.004)
Entrant x 2006	-0.046	-0.087	-0.073	0.108*	0.010	-0.012
	(0.046)	(0.053)	(0.062)	(0.063)	(0.036)	(0.024)
Entrant x 2007	-0.052	-0.054	-0.088	0.068	-0.029	-0.024
	(0.046)	(0.051)	(0.062)	(0.065)	(0.043)	(0.021)
Entrant x 2008	-0.082*	-0.080	-0.087*	0.138***	0.037	0.001
	(0.046)	(0.051)	(0.050)	(0.050)	(0.059)	(0.020)
Entrant x 2009	-0.065	-0.120**	-0.101	0.139**	0.025	0.004
	(0.051)	(0.061)	(0.073)	(0.055)	(0.037)	(0.022)
Entrant x 2010	-0.117**	-0.175***	-0.114*	0.049	0.026	-0.030
	(0.059)	(0.054)	(0.061)	(0.064)	(0.038)	(0.027)

	1	2	3	4	5	6
	COMPLEXPS	NRCOG	INTERCOMP	RMAN	OFFSH	COMPPROB
Entrant x 2011	-0.126**	-0.110*	-0.161**	0.128*	0.082*	-0.025
	(0.057)	(0.06)	(0.074)	(0.076)	(0.049)	(0.031)
Entrant x 2012	-0.136**	-0.133**	-0.155**	0.185**	-0.021	-0.020
	(0.063)	(0.065)	(0.071)	(0.079)	(0.066)	(0.027)
Entrant x 2013	-0.120***	-0.126**	-0.164***	0.194***	-0.006	-0.029
	(0.048)	(0.060)	(0.053)	(0.054)	(0.048)	(0.024)
Fixed Effects	|----------------------------------MSA, NAICS4, Size Class-------------------------------------|					
N	114855	114855	114855	114855	114855	114855
Adj. R-sq	0.452	0.349	0.387	0.217	0.313	0.149

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 3: Persistence of Initial Skill

This table presents estimates from the following regression: Future Skill Rank=α+β_1Initial Skill Rank+β_2Initial Size + MSA x year dummies + NAICS4 x Year Dummies + Elapsed Time Dummies + ε. Skill is one of 6 different measures of human capital – COMPLEXPS, NRCOG, INTERCOMP, RMAN, OFFSH, and COMPPROB that are defined in detail in Appendix A1. Future Skill Rank is the percentile skill rank of the firm based on its position in the distribution of skills in the full sample of manufacturing firms in that year. Initial Skill Rank is the percentile skill rank of the firm based on its position in the year the firm first appears in the OES sample. Initial Size is the number of employees at the time of entry. Elapsed time is the time from the year of first appearance in the OES data. MSA dummies are Metropolitan Statistical area dummies. Industry dummies are 4-digit NAICS 2007 dummies. All regressions are weighted by the sampling weights and are estimated using ordinary least squares. Standard errors are clustered by firm.

Panel A: Pooled Regressions for Entrants

	1	2	3	4	5	6
	Rank_ COMPLEXPS	Rank_ NRCOG	Rank_ INTERCOMP	Rank_ RMAN	Rank_ OFFSH	Rank_ COMPPROB
Irank_COMPLEXPS	0.297***					
	(0.071)					
Irank_NRCOG		0.282***				
		(0.078)				
Irank_INTERCOMP			0.313***			
			(0.073)			
Irank_RMAN				0.350***		
				(0.066)		
Irank_OFFSH					0.241***	
					(0.063)	
Irank_COMPPROB						0.162**
						(0.064)
Fixed Effects	|--------------------MSA x Year, NAICS4 x Year, Elapsed Time---------------|					
N	772	772	772	772	772	772
Adj. R-sq	0.633	0.575	0.630	0.553	0.509	0.426

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Panel B: Pooled Regressions for Incumbents

	1	2	3	4	5	6
	Rank_ COMPLEXPS	Rank_ NRCOG	Rank_ INTERCOMP	Rank_ RMAN	Rank_ OFFSH	Rank_ COMPPROB
Irank_COMPLEXPS	0.313***					
	(0.008)					
Irank_NRCOG		0.299***				
		(0.008)				
Irank_INTERCOMP			0.397***			
			(0.008)			
Irank_RMAN				0.372***		
				(0.008)		
Irank_OFFSH					0.309***	
					(0.008)	
Irank_COMPPROB						0.282***
						(0.008)
Fixed Effects	|-----------------------MSA x Year, NAICS4 x Year, Elapsed Time---------------|					
N	40871	40871	40871	40871	40871	40871
Adj. R-sq	0.475	0.407	0.500	0.311	0.362	0.226

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 4: Initial Skill and Firm Growth – Entrants vs. Incumbents

This table presents estimates from the following regression: Growth=$\alpha+\beta_1$Initial Skill Rank+β_2Initial Size + Age Dummies + Industry Dummies + MSA Dummies + Year Dummies + MSA x Year Dummies + Industry x Year Dummies + ε. Skill is one of 6 different measures of human capital COMPLEXPS, NRCOG, INTERCOMP, RMAN, OFFSH, and COMPPROB that are defined in detail in Appendix A1. Initial Skill Rank is the percentile skill rank of the firm based on its skill position in the year the establishment first appears in the OES sample. Growth is the annual employment growth rate of each firm. Initial Size is the number of employees at the time of entry (age 0) in Panel A and at the time the incumbent first appears in OES database in panels B and C. MSA dummies are Metropolitan Statistical area dummies. Industry dummies are 4-digit NAICS 2007 dummies. All regressions are weighted by the sampling weights and are estimated using ordinary least squares. Standard errors are clustered by firm.

Panel A: Entrants

	1	2	3	4	5	6	7	8	9	10	11	12
	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth
Irank_COMPLEXPS	0.043**						0.031					
	(0.018)						(0.022)					
Irank_NRCOG		0.036*						0.016				
		(0.019)						(0.022)				
Irank_INTERCOMP			0.053***						0.024			
			(0.018)						(0.022)			
Irank_RMAN				-0.001						0.031		
				(0.018)						(0.020)		
Irank_OFFSH					-0.063***						-0.054***	
					(0.018)						(0.020)	
Irank_COMPPROB						0.001						0.023
						(0.018)						(0.019)
Fixed Effects	|----------------------- MSA, Year ---------------|						|--------------------MSA, Year, NAICS4 ---------------|					
N	16254	16254	16254	16254	16254	16254	16254	16254	16254	16254	16254	16254
Adj. R-sq	0.048	0.048	0.049	0.048	0.049	0.048	0.053	0.052	0.053	0.053	0.053	0.053

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Panel B: Incumbents

	1	2	3	4	5	6	7	8	9	10	11	12
	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth
Irank_COMPLEXPS	0.016***						0.006***					
	(0.002)						(0.002)					
Irank_NRCOG		0.021***						0.011***				
		(0.002)						(0.002)				
Irank_INTERCOMP			0.027***						0.015***			
			(0.002)						(0.002)			
Irank_RMAN				-0.010***						-0.003*		
				(0.002)						(0.002)		
Irank_OFFSH					-0.006***						0.002	
					(0.002)						(0.002)	
Irank_COMPPROB						-0.005***						0.000
						(0.002)						(0.002)
Fixed Effects		| ------------------------ MSA, Year ---------------------|					| -------------------- MSA, Year, NAICS4 ---------------------|				
N	310861	310861	310861	310861	310861	310861	310861	310861	310861	310861	310861	310861
Adj. R-sq	0.033	0.034	0.034	0.033	0.033	0.033	0.038	0.039	0.039	0.038	0.038	0.054

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Panel C: Incumbents

	7	8	9	10	11	12
	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth
Irank_COMPLEXPS	0.006***					
	(0.002)					
Irank_NRCOG		0.010***				
		(0.002)				
Irank_INTERCOMP			0.014***			
			(0.002)			
Irank_RMAN				-0.003		
				(0.002)		
Irank_OFFSH					0.002	
					(0.002)	
Irank_COMPPROB						0.000
						(0.002)
Fixed Effects	|-------------------- MSA x Year, NAICS4 x Year---------------------|					
N	310854	310854	310854	310854	310854	310854
Adj. R-sq	0.054	0.054	0.054	0.054	0.054	0.066

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 5: Skill and China Shock – Instrumental Variable Regressions

Panel A presents estimates from the following regression: Skill=$\alpha+\beta_1$Entrant+ β_2Imports+ β_3Imports x Entrant + β_4 Entrant x Year + β_5Initial Size Class Dummies + MSA Dummies + Industry Dummies + Year Dummies + ε. Skill is one of 6 different measures of human capital - COMPLEXPS, NRCOG, INTERCOMP, RMAN, OFFSH, and COMPPROB that are defined in detail in the Web Appendix. Skill is measured for entrants anytime in the first 2 years of age and for incumbents when the establishment first appears in the sample. In both panels, Imports is the value of Chinese Imports in each industry in the US scaled by initial absorption in that industry in 2005, instrumented by the value of Chinese imports in each industry in eight other developed countries scaled by initial absorption in that industry in 2000. Initial Industry Absorption is defined as Shipments + Imports – Exports. MSA dummies are Metropolitan Statistical area dummies. Industry dummies are 4-digit NAICS 2007 dummies. All regressions are estimated using sampling weights and standard errors are clustered by industry. In Panel B we present estimates only for entrant sample and in panel C we present estimates only for incumbent sample.

Panel A: Entrants and Incumbents

	1	2	3	4	5	6
	COMPLEXPS	NRCOG	INTERCOMP	RMAN	OFFSH	COMPPROB
Entrant	0.048**	0.021	0.014	0.016	-0.043	0.016
	(0.023)	(0.024)	(0.035)	(0.037)	(0.034)	(0.018)
Imports	0.680	0.735*	0.537	-0.763	-0.935	-0.070
	(0.510)	(0.418)	(0.585)	(0.648)	(0.615)	(0.166)
Entrant x Imports	-0.652**	-0.632***	-0.483*	0.606*	0.533*	-0.087*
	(0.276)	(0.217)	(0.266)	(0.355)	(0.319)	(0.052)
Fixed Effects	|----------------------4-digit NAICS, Year, MSA, Size class------------------|					
N	87320	87320	87320	87320	87320	87320

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Panel B: Entrants Only

	1	2	3	4	5	6
	COMPLEXPS	NRCOG	INTERCOMP	RMAN	OFFSH	COMPPROB
Imports	0.856	-0.066	-2.211*	3.235***	-4.443***	0.248
	(1.131)	(1.057)	(1.224)	(1.186)	(1.404)	(0.425)
Fixed Effects	|---------------------------4-digit NAICS, Year, MSA, Size class---------------------------|					
N	2479	2479	2479	2479	2479	2479

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Panel C: Incumbents Only

	1	2	3	4	5	6
	COMPLEXPS	NRCOG	INTERCOMP	RMAN	OFFSH	COMPPROB
Imports	0.774**	0.673**	0.562*	-0.744**	-0.575**	0.009
	(0.252)	(0.337)	(0.335)	(0.356)	(0.249)	(0.087)
Fixed Effects	|---------------------------4-digit NAICS, Year, MSA, Size class---------------------------|					
N	108516	108516	108516	108516	108516	108516

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 6: Skill and China Shock – Industry Sub-Samples

This Table presents estimates from the following regression: Skill=α+β_1Entrant+ β_2Imports+ β_3Imports x Entrant + β_4 Entrant x Year + β_5Initial Size Class Dummies + MSA Dummies + Industry Dummies + Year Dummies + ε. Skill is one of 6 different measures of human capital - COMPLEXPS, NRCOG, INTERCOMP, RMAN, OFFSH, and COMPPROB that are defined in detail in the Web Appendix. Skill is measured for entrants anytime in the first 2 years of age and for incumbents when the establishment first appears in the sample. Imports is the value of Chinese Imports in each industry in the US scaled by initial absorption in that industry in 2005, instrumented by the value of Chinese imports in each industry in eight other developed countries scaled by initial absorption in that industry in 2000. Initial Industry Absorption is defined as Shipments + Imports – Exports. MSA dummies are Metropolitan Statistical area dummies. Industry dummies are 4-digit NAICS 2007 dummies. Low Skill and High Skill industries are defined on the basis of median industry skill over the period 2005-2013.All regressions are estimated using sampling weights and standard errors are clustered by industry.

	1	2	3	4	5	6
	COMPLEXPS		NRCOG		INTERCOMP	
	Low Skill	High Skill	Low Skill	High Skill	Low Skill	High Skill
Imports	0.881	-0.060	0.787*	0.443	1.520***	-1.018**
	(0.543)	(0.785)	(0.466)	(0.600)	(0.502)	(0.405)
Entrant x Imports	-0.678**	0.369	-0.646***	0.073	-0.627*	-0.112
	(0.259)	(0.552)	(0.195)	(0.769)	(0.326)	(0.595)
Entrant	0.057	0.016	0.039	-0.040	0.112**	-0.090***
	(0.034)	(0.039)	(0.031)	(0.046)	(0.051)	(0.032)
Fixed Effects	|----------------------------4-digit NAICS, Year, MSA, Size class --------------------------------|					
N	37742	49568	40409	46901	38255	49060

	7	8	9	10	11	12
	RMAN		OFFSH		COMPPROB	
	Low Skill	High Skill	Low Skill	High Skill	Low Skill	High Skill
Imports	0.592	-1.758***	1.970	-1.258**	0.335*	-0.380**
	(0.967)	(0.562)	(2.219)	(0.603)	(0.197)	(0.143)
Entrant x Imports	-0.136	0.662**	1.082***	0.469	-0.128	-0.035
	(0.756)	(0.282)	(0.401)	(0.355)	(0.103)	(0.051)
Entrant	0.099	-0.052	-0.029	-0.064	0.040**	-0.010
	(0.061)	(0.034)	(0.051)	(0.044)	(0.016)	(0.030)
Fixed Effects	|----------------------------4-digit NAICS, Year, MSA, Size class --------------------------------|					
N	50790	36520	40387	46927	44946	42370

Table 7: Initial Skill, Firm Growth and China Shock – Instrumental Variable Regressions

This table presents estimates from the following regression: Growth=α+$\beta_1\Delta$Imports+ β_2Initial Skill + $\beta_3\Delta$Imports x Initial Skill + β_4Initial Size + State Dummies + Industry Dummies + ε. Skill is one of 6 different measures of human capital – COMPLEXPS, NRCOG, INTERCOMP, RMAN, OFFSH, and COMPPROB that are defined in detail in Appendix A1. Skill is measured for entrants anytime in the first 2 years of age and for incumbents when the establishment first appears in the sample. In both panels, ΔImports is the annual change in the value of Chinese Imports in each industry in the US scaled by lagged employment in that industry, instrumented by the annual change in the value of Chinese imports in each industry in eight other developed countries scaled by lagged employment in that industry. Growth is the annual employment growth rate of each firm. Initial Size is the number of employees at the time of entry. All regressions are weighted by the sampling weights and standard errors are clustered by firm.

Panel A: Entrants

	1	2	3	4	5	6
	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth
Skill	COMPLEXPS	NRCOG	INTERCOMP	RMAN	OFFSH	COMPPROB
ΔImports	-1.354	-1.926	0.854	3.203	5.019	1.044
	(1.909)	(1.456)	(1.815)	(3.521)	(3.695)	(3.499)
Initial Skill Rank	0.022	0.007	0.042*	0.021	-0.041*	0.017
	(0.023)	(0.024)	(0.025)	(0.020)	(0.023)	(0.022)
ΔImports x Initial Skill Rank	0.061**	0.072**	0.015	-0.033	-0.057	0.015
	(0.033)	(0.031)	(0.019)	(0.031)	(0.036)	(0.034)
Fixed Effects	|---------------------------------Year, MSA, NAICS4---------------------------------|					
N	15780	15780	15780	15780	15780	15780

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Panel B: Incumbents

	1	2	3	4	5	6
	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth
Skill	COMPLEXPS	NRCOG	INTERCOMP	RMAN	OFFSH	COMPPROB
ΔImports	-0.362	-0.168	0.146	1.443**	2.512***	1.221*
	(0.431)	(0.545)	(0.911)	(0.617)	(0.819)	(0.685)
Initial Skill Rank	0.001	0.006**	0.011***	-0.003	0.005*	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
ΔImports x Initial Skill Rank	0.033***	0.029***	0.023**	-0.002	-0.022***	0.002
	(0.006)	(0.006)	(0.010)	(0.006)	(0.007)	(0.004)
Fixed Effects	|---Year, MSA, NAICS4---|					
N	303065	303065	303065	303065	303065	303065

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 8: Initial Skill, Firm Growth and China Shock – Instrumental Variable Regressions

This table presents estimates from the following regression: Growth=α+β_1ΔImports+ β_2Initial Skill + β_3ΔImports x Initial Skill + β_4Initial Size + MSA Dummies + Year Dummies + ε. In Panels A and C, skill is one of the following measures of human capital – COMPLEXPS, NRCOG, or INTERCOMP and in panels B and D, skill is one of the following measures of human capital – RMAN, OFFSH, or COMPPROB. Skill is measured for entrants anytime in the first 2 years of age and for incumbents when the establishment first appears in the sample. ΔImports is the annual change in the value of Chinese Imports in each industry in the US over the periods 2005-2007, 2007-2010, and 2010-2013 scaled by employment at the beginning of the period in each case in that industry, instrumented by the change in the value of Chinese imports over the corresponding period in each industry in eight other developed countries scaled by employment in that industry at the beginning of the period. Growth is the annual employment growth rate of each firm. Initial Size is the number of employees at the time of entry. All regressions are weighted by the sampling weights and standard errors are clustered by firm.

Panel A: Entrants

	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth
Skill	**COMPLEXPS**			**NRCOG**			**INTERCOMP**		
	2005-2008	**2008-2010**	**2010-2013**	**2005-2008**	**2008-2010**	**2010-2013**	**2005-2008**	**2008-2010**	**2010-2013**
Initial Skill	-20.378	-1.903	-1.500	-17.048	-2.004	-0.387	-3.956	0.148	1.001
	(33.898)	(2.134)	(3.472)	(23.015)	(2.018)	(3.197)	(13.930)	(2.993)	(3.264)
ΔImports	-0.023	0.060	-0.036	-0.044	0.034	0.008	0.008	0.046	0.052*
	(0.141)	(0.041)	(0.037)	(0.093)	(0.038)	(0.034)	(0.082)	(0.034)	(0.030)
Initial Skill x ΔImport	0.236	0.079**	0.066	0.201	0.088***	0.045	0.036	0.042*	0.014
	(0.340)	(0.040)	(0.055)	(0.231)	(0.030)	(0.047)	(0.158)	(0.023)	(0.037)
N	4441	5915	9230	4441	5915	9230	4441	5915	9230

	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth
Skill	**RMAN**			**OFFSH**			**COMPPROB**		
	2005-2008	**2008-2010**	**2010-2013**	**2005-2008**	**2008-2010**	**2010-2013**	**2005-2008**	**2008-2010**	**2010-2013**
Initial Skill	2.250	4.386	3.839	4.033	5.548	5.589	-3.495	3.552	0.132
	(5.355)	(3.200)	(4.944)	(7.462)	(3.694)	(4.982)	(5.611)	(3.182)	(4.901)
ΔImports	0.078	-0.018	0.034	0.009	-0.053*	-0.036	-0.013	0.001	0.017
	(0.081)	(0.030)	(0.031)	(0.072)	(0.031)	(0.029)	(0.040)	(0.028)	(0.031)
Initial Skill x ΔImport	-0.118	-0.045	-0.043	-0.113	-0.057	-0.061	0.053	-0.018	0.036
	(0.170)	(0.031)	(0.052)	(0.108)	(0.037)	(0.054)	(0.079)	(0.027)	(0.049)
N	4441	5915	9230	4441	5915	9230	4441	5915	9230

Panel B: Incumbents

	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth
Skill	**COMPLEXPS**			**NRCOG**			**INTERCOMP**		
	2005-2008	**2008-2010**	**2010-2013**	**2005-2008**	**2008-2010**	**2010-2013**	**2005-2008**	**2008-2010**	**2010-2013**
Initial Skill	-196.728	22.650	-11.206	-235.148	54.788	1.221	-66.941	93.318	2.030
	(162.410)	(75.655)	(68.618)	(144.644)	(92.253)	(73.805)	(115.512)	(120.230)	(120.457)
ΔImports(2010-2013)	0.020*	0.007	-0.008**	0.028***	0.015***	-0.006*	0.038***	0.021***	-0.006
	(0.011)	(0.005)	(0.004)	(0.008)	(0.004)	(0.004)	(0.007)	(0.004)	(0.006)
Initial Skill x ΔImport	3.800	3.268***	2.434***	4.441*	2.620**	2.141***	1.755	2.025	2.323*
	(3.140)	(1.068)	(0.459)	(2.599)	(1.050)	(0.506)	(1.440)	(1.528)	(1.227)
N	68039	120361	194167	68039	120361	194167	68039	120361	194167

	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth
Skill	**RMAN**			**OFFSH**			**COMPPROB**		
	2005-2008	**2008-2010**	**2010-2013**	**2005-2008**	**2008-2010**	**2010-2013**	**2005-2008**	**2008-2010**	**2010-2013**
Initial Skill	124.906	180.555**	121.180	56.517	314.193***	197.882*	-8.512	174.313*	95.629
	(110.896)	(88.300)	(80.979)	(122.788)	(78.322)	(105.247)	(56.126)	(95.866)	(82.385)
ΔImports(2010-2013)	-0.020***	-0.006	0.009***	0.011*	0.001	0.003	-0.002	0.002	-0.001
	(0.007)	(0.005)	(0.003)	(0.006)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)
Initial Skill x ΔImport	-2.310	0.344	-0.126	-0.506	-2.489***	-1.586**	0.868	0.498	0.395
	(1.418)	(0.887)	(0.518)	(1.301)	(0.613)	(0.681)	(1.085)	(0.492)	(0.646)
N	68039	120361	194167	68039	120361	194167	68039	120361	194167

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Table 9: New Plants versus Entrants

This table presents estimates from the following regression: Skill=α+β_1New Plant+ β_2Imports+ β_3Imports x New Plant + β_5Initial Size Class Dummies + MSA Dummies + Year Dummies + ε. Skill is one of 6 different measures of human capital - COMPLEXPS, NRCOG, INTERCOMP, RMAN, OFFSH, and COMPPROB that are defined in detail in the Web Appendix. Skill is measured for entrants and new plants anytime in the first 2 years of age. Entrants are single establishment entrants whereas New Plants are new establishments of existing multi-establishment firms. Imports is the value of Chinese Imports in each industry in the US scaled by initial absorption in that industry in 2005, instrumented by the value of Chinese imports in each industry in eight other developed countries scaled by initial absorption in that industry in 2000. Initial Industry Absorption is defined as Shipments + Imports – Exports. MSA dummies are Metropolitan Statistical area dummies. All regressions are estimated using sampling weights and standard errors are clustered by industry.

	1	2	3	4	5	6
	COMPLEXPS	NRCOG	INTERCOMP	RMAN	OFFSH	COMPPROB
Imports	-2.636***	-1.559***	-1.055*	1.520**	2.264***	0.028
	(0.876)	(0.536)	(0.620)	(0.626)	(0.640)	(0.085)
New Plant	0.040	0.051	0.066	-0.043	-0.052	0.017
	(0.070)	(0.049)	(0.062)	(0.059)	(0.054)	(0.014)
New Plant x Imports	2.107**	0.950	0.685	-1.054	-1.086**	-0.330**
	(1.007)	(0.659)	(0.672)	(0.791)	(0.534)	(0.165)
Fixed Effects	|--MSA, Year, Sizeclass--|					
N	3494	3494	3494	3494	3494	3494

Appendix A1: Summary Statistics and Correlations

Panel A:

Variable	N	Mean	Std. Dev.	Min	Max
Entrant	153298	0.048	0.215	0	1
COMPLEXPS	153298	0.118	0.563	-1.588	2.940
NRCOG	153298	-0.365	0.487	-2.253	3.227
INTERCOMP	153298	-0.046	0.580	-1.784	2.906
RMAN	153298	0.603	0.609	-1.785	2.588
OFFSH	153298	0.334	0.524	-3.297	3.854
COMPPROB	153298	-0.094	0.305	-2.061	2.584
Entrant Growth	16295	9.33	63.36	-100	560
Incumbent Growth	304971	-0.44	21.89	-82.35	100

Panel B: Correlations

	COMPLEXPS	NRCOG	INTERCOMP	RMAN	OFFSH
NRCOG	0.711***				
INTERCOMP	0.463***	0.599***			
RMAN	-0.390***	-0.468***	-0.568***		
OFFSH	-0.202***	-0.197***	0.155***	-0.236***	
COMPPROB	0.084***	0.171***	0.068***	0.066***	-0.124***

Appendix Table A2: Regressions by Spell for Entrants

	1	2	3	4	5	6
Time Elapsed (years)	3	4	5	6	7	7+
IRank_COMPLEXPS	0.436***	0.563***	0.479***	0.639***	0.500***	0.702***
	(0.037)	(0.042)	(0.147)	(0.094)	(0.105)	(0.084)
N	1204	439	195	321	156	75
adj. R-sq	0.251	0.356	0.434	0.375	0.294	0.599
Irank_NRCOG	0.427***	0.558***	0.383***	0.475***	0.418**	0.786***
	(0.044)	(0.042)	(0.103)	(0.113)	(0.180)	(0.209)
N	1204	439	195	321	156	75
adj. R-sq	0.269	0.330	0.325	0.286	0.121	0.612
Irank_INTERCOMP	0.533***	0.693***	0.704***	0.548***	0.595***	0.892***
	(0.076)	(0.065)	(0.065)	(0.078)	(0.187)	(0.133)
N	1204	439	195	321	156	75
adj. R-sq	0.344	0.488	0.595	0.529	0.359	0.543
Irank_RMAN	0.627***	0.428***	0.519***	0.473***	0.151	0.797***
	(0.045)	(0.079)	(0.077)	(0.080)	(0.197)	(0.223)
N	1204	439	195	321	156	75
Adj. R-sq	0.427	0.302	0.436	0.312	0.229	0.452
Irank_OFFSH	0.506***	0.429***	0.502***	0.389***	0.371***	0.145
	(0.058)	(0.106)	(0.109)	(0.130)	(0.114)	(0.429)
N	1204	439	195	321	156	75
Adj. R-sq	0.263	0.226	0.337	0.238	0.179	0.281
Irank_COMPPROB	0.368***	0.424***	0.504***	0.317**	0.267	0.649***
	(0.081)	(0.077)	(0.089)	(0.118)	(0.246)	(0.073)
N	1204	439	195	321	156	75
Adj. R-sq	0.211	0.229	0.372	0.289	0.093	0.580

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Appendix Table A3: Non-linearity in Initial Skill and Firm Growth – Entrants vs. Incumbents

Panel A presents estimates from the following regression: Growth=$\alpha+\beta_1$Initial Skill Rank(11-50)+ β_2Initial Skill Rank(51-90)+ β_3Initial Skill Rank(91-100)+β_4Initial Size + Age Dummies + Industry Dummies + MSA Dummies + Year Dummies + ε. Skill is one of 6 different measures of human capital COMPLEXPS, NRCOG, INTERCOMP, RMAN, OFFSH, and COMPPROB that are defined in detail in Appendix A1. Initial Skill Rank is the percentile skill rank of the firm based on its skill position in the year the first appears in the OES sample. We create 4 dummies based on whether the percentile rank is ≤10 (omitted category), 11-50, 51-90, and 91-100. Growth is the annual employment growth rate of each firm. Initial Size is the number of employees at the time of entry. MSA dummies are Metropolitan Statistical area dummies. Industry dummies are 4-digit NAICS 2007 dummies. All regressions are weighted by the sampling weights and are estimated using ordinary least squares. Standard errors are clustered by firm.

Panel A: Entrants

	1	2	3	4	5	6	7	8	9	10	11	12
	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth
Irank(11-50) _COMPLEXPS	4.581**						5.542**					
	(2.088)						(2.257)					
Irank(51-90) _COMPLEXPS	5.591***						6.111***					
	(2.056)						(2.344)					
Irank(91-100) _COMPLEXPS	6.981***						7.034**					
	(2.578)						(2.916)					
Irank(11-50)_NRCOG		2.199						2.120				
		(1.940)						(2.026)				
Irank(51-90)_NRCOG		2.67						1.897				
		(1.95)						(2.125)				
Irank(91-100)_NRCOG		5.026**						3.719				
		(2.512)						(2.728)				
Irank(11-50) _INTERCOMP			2.065						0.341			
			(1.861)						(1.940)			
Irank(51-90) _INTERCOMP			4.417**						1.363			
			(1.849)						(2.067)			
Irank(91-100) _INTERCOMP			4.165*						1.383			
			(2.453)						(2.673)			

	1	2	3	4	5	6	7	8	9	10	11	12
	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth
Irank(11-50)_RMAN				0.301						0.815		
				(1.963)						(2.011)		
Irank(51-90)_RMAN				0.627						2.151		
				(1.961)						(2.042)		
Irank(91-100)_RMAN				-0.521						3.052		
				(2.451)						(2.616)		
Irank(11-50)_OFFSH					1.087						1.756	
					(1.777)						(1.790)	
Irank(51-90)_OFFSH					-1.523						-0.73	
					(1.769)						(1.851)	
Irank(91-100)_OFFSH					-4.534**						-2.465	
					(2.235)						(2.438)	
Irank(11-50) _COMPPROB						0.920						2.415
						(1.748)						(1.922)
Irank(51-90) _COMPPROB						0.578						2.453
						(1.918)						(2.096)
Irank(91-100) _COMPPROB						2.679						4.954*
						(2.449)						(2.556)
Fixed Effects	|-------------------------------MSA, Year-------------------------------|						|------------------------MSA, Year, NAICS4------------------------|					
N	16254	16254	16254	16254	16254	16254	16254	16254	16254	16254	16254	16254
Adj. R-sq	0.049	0.048	0.048	0.048	0.049	0.048	0.052	0.052	0.052	0.053	0.053	0.053

*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Panel B: Incumbents

	1	2	3	4	5	6	7	8	9	10	11	12
	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth
Irank(11-50) _COMPLEXPS	0.415**						0.394*					
	(0.187)						(0.205)					
Irank(51-90) _COMPLEXPS	1.171***						0.764***					
	(0.185)						(0.220)					
Irank(91-100) _COMPLEXPS	1.277***						0.487*					
	(0.230)						(0.267)					
Irank(11-50)_NRCOG		0.529***						0.589***				
		(0.185)						(0.196)				
Irank(51-90)_NRCOG		1.415***						0.967***				
		(0.184)						(0.205)				
Irank(91-100)_NRCOG		1.758***						0.959***				
		(0.230)						(0.256)				
Irank(11-50) _INTERCOMP			1.298***						0.813***			
			(0.187)						(0.195)			
Irank(51-90) _INTERCOMP			2.263***						1.260***			
			(0.185)						(0.206)			
Irank(91-100) _INTERCOMP			2.248***						1.064***			
			(0.231)						(0.255)			
Irank(11-50)_RMAN				0.251						0.236		
				(0.184)						(0.187)		
Irank(51-90)_RMAN				-0.05						0.156		
				(0.184)						(0.193)		
Irank(91-100)_RMAN				-1.186***						-0.617**		
				(0.235)						(0.245)		
Irank(11-50)_OFFSH					0.816***						0.533***	
					(0.176)						(0.183)	

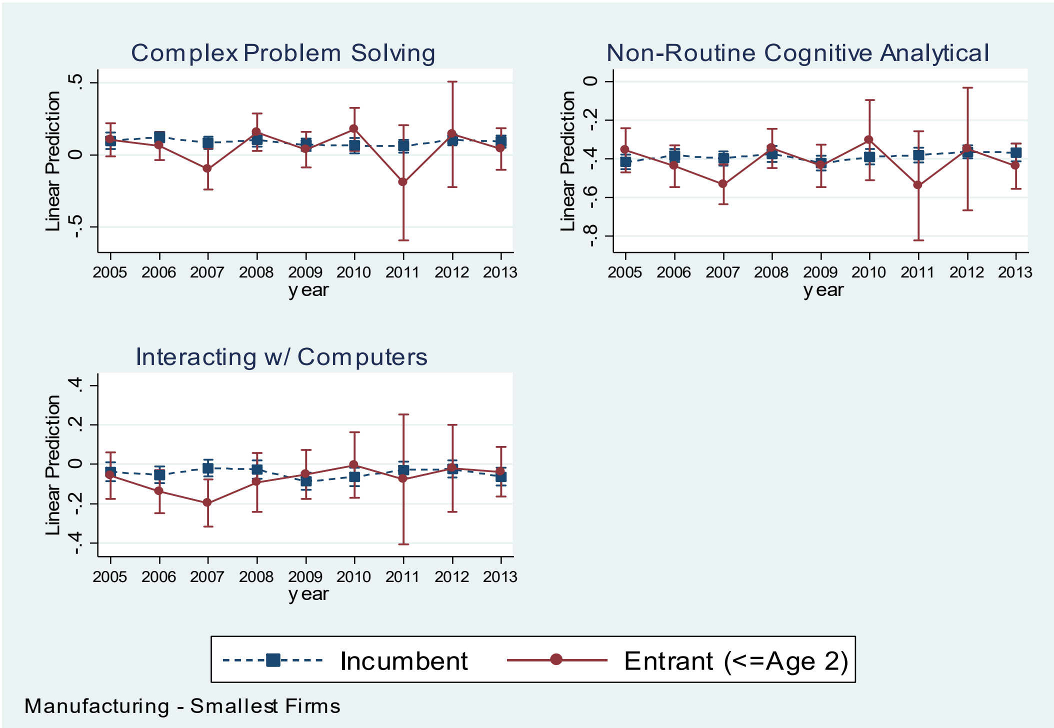
	1	2	3	4	5	6	7	8	9	10	11	12
	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth	Firm Growth
Irank(51-90)_OFFSH					0.520***						0.490***	
					(0.176)						(0.188)	
Irank(91-100)_OFFSH					-0.578***						0.300	
					(0.231)						(0.253)	
Irank(11-50) _COMPPROB						-0.030						0.100
						(0.161)						(0.170)
Irank(51-90) _COMPPROB						-0.329**						0.061
						(0.163)						(0.173)
Irank(91-100) _COMPPROB						-0.602						-0.139
						(0.219)						(0.225)
Fixed Effects	|--------------------------------MSA, Year--------------------------------|						|-------------------------MSA, Year, NAICS4-------------------------|					
N	310861	310861	310861	310861	310861	310861	310861	310861	310861	310861	310861	310861
Adj. R-sq	0.033	0.034	0.034	0.033	0.033	0.033	0.038	0.039	0.039	0.039	0.038	0.038

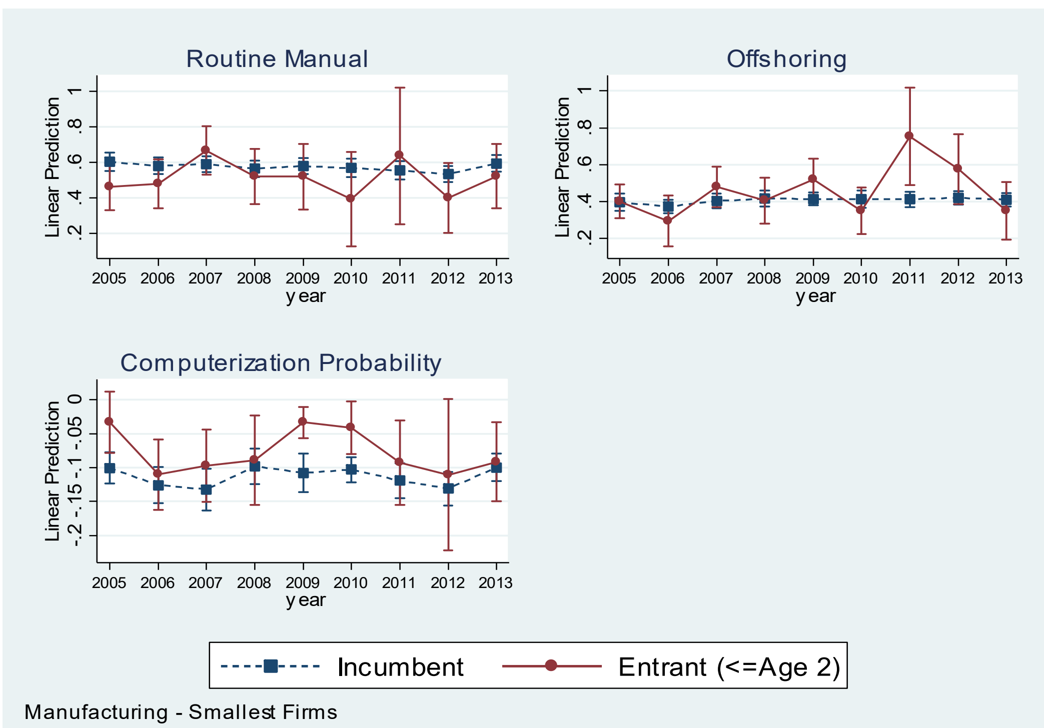
*, **, and *** represent significance at the 10%, 5%, and 1% levels respectively.

Appendix Table A4: Initial Skill and Exit (To be disclosed)

Logits with MSA and Year FE and Industry Clustering. DV is 1 in year of exit and 0 otherwise.

Appendix A5


Complex Problem Solving
Non-Routine Cognitive Analytical
Interacting w/ Computers
Linear Prediction
year
2005 2006 2007 2008 2009 2010 2011 2012 2013
Incumbent
Entrant (<=Age 2)
Manufacturing - Smallest Firms


Routine Manual
Offshoring
Computerization Probability
Linear Prediction
year
2005 2006 2007 2008 2009 2010 2011 2012 2013
Incumbent
Entrant (<=Age 2)
Manufacturing - Smallest Firms

Web Appendix

Occupational Employment Statistics (OES) and Quarterly Census of Employment and Wages (QCEW)

The OES provides detailed data on the employment and wage rates of workers in each occupation in U.S. establishments.[22] The OES program surveys U.S. establishments on a three-year cycle. During each survey, a sample (referred to as a "*Panel*") of approximately 200,000 establishments is drawn semiannually so that over the course of three-years, approximately 1.2 million establishments are sampled. Establishments selected in any one panel are not sampled again in the next five succeeding panels. For instance, the OES data for the 2008 survey includes establishments that were sampled in 2005-Q4, 2006-Q2, 2006-Q4, 2007-Q2, 2007-Q4, or 2008-Q2. The aggregated sample across six panels in conjunction with the sampling weights represents the entire population of firms.

The OES sample frame is constructed from a sampling universe of approximately 6.8 million nonfarm establishments that file unemployment insurance (UI) reports to the State workforce agencies. Employers are required by law to file these reports to the State where each establishment is located. The establishments in the sample frame are stratified by Geography (State x MSA[23]) and Industry (NAICS 4/5). The average response rate in the OES survey for our time period is above 75%.[24]

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[22] An establishment is defined as a single physical location at which economic activity occurs (e.g., a store, a factory, a restaurant, etc.). Each establishment is assigned a six-digit NAICS code. When a single physical

[23] Most states also specify up to four residual balance-of-State (BOS) areas to cover the remaining non-MSA portion of the State. While we include the establishments in the BOS area in our analysis, restricting the sample to just MSA does not change our results.

[24] The allocation of sample to strata is described in the BLS Handbook of Methods as follows: "Each State is assigned a fixed overall sample size. The frame is stratified into nonempty State-by- MSA/BOS-by-NAICS4/5 strata. Each time a sample is selected, a six-panel allocation of the 1.2 million sample units among these strata is performed. The largest establishments are removed from the allocation because they will be selected with certainty

We construct annual panels of the OES data from 2005-2013 with annual sampling weights. We restrict our sample to only private establishments (dropping Federal and State Government establishments) and also drop establishments from Guam which are not covered by the UI program. All of our analysis is conducted on establishments that are stand-alone and not identified as belonging to a part of multi-establishment firm. Single establishment firms make up more than 80% of our sample. However in robustness tests we benchmark our results against new plants of multi-establishment firms.

To the OES data, we merge information on birth of the firm from the Quarterly Census of Employment and Wages (QCEW), a census of monthly employment and quarterly wage information by 6-digit NAICS industry in the U.S. The birth of the firm is recognized as the date of first non-zero employment. QCEW also allows us to identify firm deaths (establishments that have gone out of business, or have had four consecutive quarters of zero employment) where the date of exit is the date of last positive employment.

Variable Construction

We restrict our OES sample to all establishments for which we have data on births from QCEW.[25] We define **Entrants** as all those establishments that are ≤ 2 years of age, i.e. the first time they appear in the OES during the sample period. BLS creates a national sampling frame every quarter by combining the UI reports of all States into a single database called the

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once during the six panel cycle. For the remaining noncertainty strata, a set of minimum sample size requirements based on the number of establishments in each cell is used to ensure coverage for industry and MSAs. For each State-by-MSA/BOS-by-NAICS4/5 stratum, a sample allocation is calculated using a power allocation influenced by employment size of each stratum and occupational variability of the industry. Thus strata with higher levels of employment are allocated more sample than strata with lower levels of employment. Industries that tend to have greater occupational variability are allocated more sample than industries that are more occupationally homogenous. The actual six-panel sample allocation is the larger of the minimum sample allocation and the power allocation."

[25] Eleven states declined to provide quarterly data on employment and wages. These include Florida, Kentucky, Massachusetts, Michigan, Mississippi, Montana, New Hampshire, New York, North Carolina, Oregon, Pennsylvania, and Wyoming.

Longitudinal Data Base (LDB). The OES sample frame is based on the LDB that is usually the quarter that is one year prior to OES's collection date. For example, the May 2008 sample was selected from the 2007-2nd quarter LDB file. Thus the first time we observe occupation-level information on the establishment in OES is when it is between four-eight quarters old. For the entrants, we get initial size (size at birth or age 0) and date of birth from QCEW while their initial skill is the first time the establishment is in OES (age≤2). **Incumbents** are establishments that are at least 3 years old when they first appear in our dataset.

We follow the entrants from the time they first appear in our sample period to the end of the sample period (i.e. 2013). Due to the nature of sampling, we have irregularly spaced panel data on skill levels. For growth, we compute an annual establishment growth rate, **Entrant Growth** using employment every 4 quarters from QCEW. **Incumbent Growth** is the annual establishment growth rate calculated for the establishments classified as incumbents in our OES sample. We drop the top and bottom 1% outliers for establishment growth in both the entrant and incumbent samples. We define four **Size Class** dummies to identify establishments with ≤ 5 employees, 6-20 employees, 21-100 employees and over 100 employees.

We restrict all our data to manufacturing firms (NAICS 2007 codes 3111-3399). We have three different NAICS transitions over our sample period. Data from 2005-2006 are classified under the NAICS 2002 system, data from 2007-2010 are classified under the NAICS 2007 system and data from 2011-2013 are classified under the NAICS2012 system. We develop concordance codes and convert all our data into NAICS 2007.

Within manufacturing we further classify industries into High-tech industries and Low-tech industries based on the classification in Goldschlag and Miranda (2016). Goldschlag and

Miranda (2016) classify High Tech Industries as those with the highest proportion of workers in occupations related to STEM (Science, Technology, Engineering, and Math) in 2005, 2012, and 2014. Their paper builds on Hecker (2005) who measures employment in technology oriented occupations to classify High-Tech industries based on the idea that firms engaged in R&D and innovation employ a large number of scientists, engineers, and technicians. Goldschlag and Miranda (2016) also show that there is a high degree of overlap in the manufacturing sector between their definition and other classifications including OECD's R&D intensive classification and classifications based on the US Census Bureau's list of advanced technology products.

As robustness, we also classify industries in the top quintile of complex problem solving skills in 2005 as high-tech industries (17 out of 86 industries) and the rest as low-tech industries.

Measures of human capital

In the OES data, workers are classified into occupations on the basis of the work they perform and skills required in each occupation. An employee who performs the duties of two or more occupations is reported in the occupation that requires the highest level of skill or in the occupation in which the employee spends the most time if there is no measurable difference in skill requirements.[26]

The occupations are defined by the Standard Occupational Classification (SOC) system that is designed to reflect the current occupational structure of the U.S. and classifies all

[26] Supervisors of professional and technical workers, team leaders, lead workers, and supervisors of production, sales, and service workers who spend at least 20 percent of their time performing work similar to the workers they supervise are classified with the workers they supervise. First-line managers and supervisors of production, service, and sales workers who spend more than 80 percent of their time performing supervisory activities are classified separately in the appropriate supervisor category, since their work activities are distinct from those of the workers they supervise. First-line managers are generally found in smaller establishments where they perform both supervisory and management functions, such as accounting, marketing, and personnel work. Thus it is not the case that all establishments with just 1 employee report occupation as CEO. In our sample, less than 0.9% of young establishments that report 1 employee are classified as CEOs.

occupations in which work is performed for pay or profit. The SOC is used by all U.S. Federal statistical agencies to classify workers into occupational categories. There were two SOC classifications in use over our sample period: SOC2000 for 2005 and 2008 data and SOC2010 for 2011 and 2014 data. We use a cross-walk between the two classifications provided by the Bureau of Labor Statistics to consistently match occupations over our sample period to the SOC 2000 classification. However we do not have earlier data on new occupations that were introduced as part of SOC2010 and these are not part of our analyses.

We capture the skill-level of the establishments using job skills data from O*NET. O*NET is a database maintained by the Department of Labor that provides data on occupation-specific descriptors that define the key features of an occupation such as worker abilities, technical skills, job output, work activities, etc. Currently, the O*NET database includes measures of the Importance and Level of more than 250 worker and occupational characteristics, on a scale of 0 to 100, for 974 occupations based on the SOC system.[27] The database is annually updated by ongoing surveys of each occupation's worker population, occupation experts, and occupation analysts. We use Version 13 of the O*NET database released in 2005 based on SOC 2000.

Following the labor market literature (e.g. Autor, Levy, and Murnane (2003) Acemoglu and Autor (2011, 2012), Costinot, Oldenski, and Rauch (2011), and Keller and Utar, 2016), we focus on the following six measures of human capital:

[27] While the O*NET is a SOC based classification, it classifies occupations into a greater level of detail. Since our OES sample is based on SOC, we do not use the disaggregated occupation-level data for the additional occupations in O*NET.

Variable	Source	Definition
Complex Problem Solving	O*NET	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.
Non-Routine Cognitive Analytical	O*NET	Mathematical Reasoning + Inductive Reasoning + Developing Objectives and Strategies + Making Decisions and Solving Problems. Source: Keller and Utar (2016)
Routine Manual	O*NET	Spend time making repetitive motions + Pace Determined by Speed of Equipment + Manual Dexterity + Finger Dexterity. Source: Keller and Utar (2016)
Interacting with Computers	O*NET	Using computers and computer systems (including hardware and software) to program, write software, set up functions, enter data, or process information.
Probability of Computerization	O*NET	Based on the following O*NET variables [*Perception and manipulation* (Finger dexterity + Manual dexterity + Cramped work space, awkward positions) + *Creative Intelligence* (Originality+Fine arts) + *Social Intelligence* (Social perceptiveness+Negotiation+Persuasion+Assisting and caring for others)] Source: Frey and Osborne (2016)
Offshoring	O*NET	Simple average of the two aggregate variables face-to-face contact and on-site job, and reverse the sign of the resulting variable. Face-to-face contact is the average value of the O*NET variables “face-to-face discussions,” “establishing and maintaining interpersonal relationships,” “assisting and caring for others,” “performing for or working directly with the public,” and “coaching and developing others.” On-site job is the average of the O*Net variables “inspecting equipment, structures, or material,” “handling and moving objects,” “operating vehicles, mechanized devices, or equipment,” and the mean of “repairing and maintaining mechanical equipment” and “repairing and maintaining electronic equipment. **Source:** Autor and Dorn (2014), Firpo, Fortin, and Lemieux (2011)

Thus COMPLEXPS and INTERCOMP are measures directly from the O*NET database whereas the others are composite measures derived from underlying scales. Following Autor and Acemoglu (2011), each constituent measure is then standardized to have mean zero and standard deviation one, using labor supply weights from the 2008 (i.e. pooled 2005/6/7) Occupational Employment Statistics (OES) Survey. The composite task measures listed above are equal to the summation of their respective constituent scales, then standardized to mean zero and standard deviation one.

To go from the occupation-level scores to the establishment level, we compute a weighted average across occupations in each firm weighting by the number of employees in each occupation. For instance, for establishment *i* with *o=1,….,O* occupations, we compute the average level of Complex Problem Solving as:

$$COMPLEXPS_i = \sum_{o=1}^{O} COMPLEXPS(o) \times Employment\ Share(o)_i \qquad (1)$$

where *Employment Share* is the employment in occupation *o* as a share of total employment in the firm. Thus a high COMPLEXPS score for a firm implies a large share of its workers employed in occupations where the tasks are non-routine. We construct similar scores for all the other skills.

Chinese Trade Shock

Following Acemoglu et al. (2016), our main measure of industry exposure to import competition is $\boldsymbol{Imports_j^{US}}$ measured as the total value of Chinese imports into the US in each 4-digit NAICS industry *j* scaled by initial absorption in that industry measured as total industry shipments, $Y_{j,2005}$ plus total imports, $M_{j,2005}$ – total exports, $E_{j,2005}$ in that industry in 2005. Thus

$$Imports_j^{US} = \frac{M_{j,t}^{China \to US}}{Y_{j,2005} + M_{j,2005} - E_{j,2005}} \qquad (2)$$

Data on US imports is available at the six-digit Harmonized System (HS) product level from the US Census Bureau and is aggregated to the NAICS industry level as in Schott (2008).[28] We use the industry concordances detailed in the web appendix to convert all the import data into NAICS 2007 4-digit industries. All the import and industry absorption data are inflated to 2009 US dollars using the Personal Consumption Expenditure (PCE deflator) downloaded from the U.S. Bureau of Economic Analysis.

[28] We thank Peter Schott for making this data available to us.

The import penetration ratio for US imports from China has increased exponentially since 2001 when China joined the World Trade Organization (WTO). Figure 1 shows the import penetration ratio for US manufacturing imports from China where import penetration ratio is defined as the ratio of Chinese Imports in manufacturing to US Gross Manufacturing Output + Total Manufacturing Imports – Total Manufacturing Exports. We see that the share of total US spending in manufacturing on Chinese goods has gone up from 4% in 2005 to 6.7% in 2013.

Our identification strategy is derived from Autor, Dorn, and Hanson (2013) and identifies the component of US import growth that is due to Chinese productivity and trade costs. Autor et. al. identify the supply-driven component of Chinese imports by instrumenting the growth in Chinese imports to the United States using contemporaneous composition and growth of Chinese imports in eight other developed countries.[29]

The identifying assumption underlying this strategy is that the surge of Chinese exports across the world is primarily driven by China-specific events: China's transition to a market-oriented economy and its accession to the WTO and the accompanying rise in its comparative advantage and falling trade costs explains the common within-industry component of rising Chinese imports to the United States and other high-income countries. Thus, by instrumenting, we are addressing reverse causality that may arise if Chinese imports into the U.S. were driven by negative domestic productivity shocks or skill shortages affecting U.S. manufacturers.

To obtain data on Chinese imports to these countries, we use the UN Comrade Database on imports at the six-digit Harmonized System (HS) product level. We convert this into NAICS 2007 codes using the HS-6 to NAICS concordance in Schott (2008) and the concordances

[29] Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

between the different NAICS classifications detailed in the Web Appendix. Thus $\boldsymbol{Imports_j^{ODC}}$ is the total value of Chinese imports into 8 other developed countries in each 4-digit NAICS industry j scaled by initial absorption in that industry in 2000. Thus

$$Imports_j^{ODC} = \frac{M_{j,t}^{China \to ODC}}{Y_{j,2000} + M_{j,2000} - E_{j,2000}} \qquad (3)$$

In the growth regressions, we replace the numerator in equations (2) and (3) with the annual change in imports, $\Delta Imports_j$. Figure A1 below plots the change in US exposure from (2) against change in other countries' exposure from (3) for all US manufacturing industries which is equivalent to the first stage regression in our growth regressions without detailed controls. The figure clearly shows strong predictive power of high import growth in other high-income countries for US import growth from China.

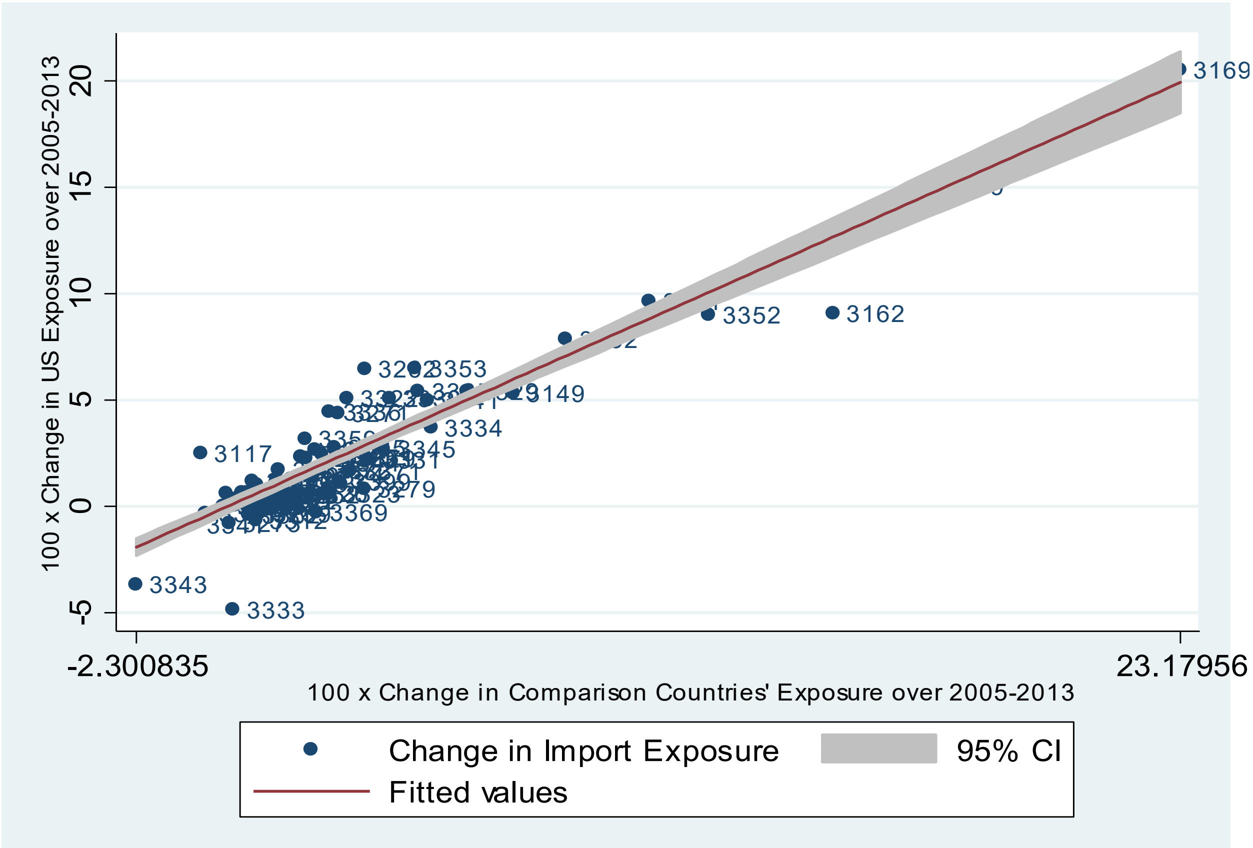

Figure A1: First-stage regression, 2005-2013. Each point represents a four-digit manufacturing industry as defined as NAICS 2007. The change in US exposure to Chinese imports is defined as the change in US imports from China divided by initial absorption in that industry (shipments + exports-imports in 2005); the change in the comparison countries' exposure to Chinese imports is defined as the change in these countries' imports from China divided by initial absorption in that industry (shipments + exports-imports in 2000).