The March of the Techies: Technology, Trade, and Job Polarization in France, 1994–2007

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Abstract

Using administrative employee-firm-level data from 1994 to 2007, we show that the labor market in France has become polarized: employment shares of high and low wage occupations have grown, while middle wage occupations have shrunk. During the same period, the share of hours worked in technology-related occupations ("techies") grew substantially, as did imports and exports, and we explore the causal links between these trends. Our paper is the first to analyze polarization in any country using firm-level data. Our data includes hours worked classified into 22 occupations, as well as imports and exports, for every private sector firm. We show that polarization is pervasive: it has occurred within the nonmanufacturing and manufacturing sectors, and both within and between firms. Motivated by the fact that technology adoption is mediated by technically qualified managers and technicians, we use an innovative measure of the propensity to adopt new technology: the firm-level employment share of techies. Using the subsample of firms that are active over the whole period, we show that firms with more techies in 2002 saw greater polarization from 2002 to 2007. Within manufacturing firms, importing causes skill upgrading while exporting causes skill downgrading within blue-collar workers. To control for the endogeneity of firm-level techies and trade in 2002, we use values of techies and trade from 1994 to 1998 as instruments. We also show that employment in firms with more techies in 2002 grew more rapidly from 2002 to 2007, using the same instrumental variable strategy. We conclude that technological change, mediated through techies, is an important cause of polarization in France. Trade is less important.

JEL classifications: J2, O3, D3, F1, F16, F66.

Keywords: Job polarization, technological change, offshoring, skill bias, firm level data.

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1 Introduction

Job polarization—growth in the shares of high-wage and low-wage jobs at the expense of middle wage jobs—is one of the most striking phenomena in many advanced economies' labor markets in the last several decades.[1]. In this paper we study the extent, characteristics, and causes of job polarization in France from 1994 to 2007.

Job polarization occurs between and within firms over time, and we are the first to study polarization using firm-level data. Studying firm-level data is important because technological change and globalization affect demand for labor through firm-level decisions. We use administrative worker-firm linked data for the entire French private sector to document how employment shares have changed across 22 major occupations, which we rank by average wage. The comprehensive nature and high quality of the French administrative data allow us to describe changes in employment shares in an unusually accurate way, compared to other research that typically relies on survey data. We use an instrumental variables strategy to make causal inferences about the importance of technology and trade in driving polarization.

We match workers with imports, exports and technology, through the firms at which they work. We construct a novel indicator for technology at the firm level: the employment share of workers who facilitate the adoption and use of new technology—the *techies*. We match customs data to firms to create import and export intensities. The matched firm-worker nature of the data allow us to study polarization along two complementary dimensions: within-firm adjustment, and changes in the employment shares across firms that have different occupational shares. In addition, we exploit the firm-worker match to construct measures of exposure to imports, exports and technology, across occupations.

We show that, like several other countries, France has experienced job polarization: employment shares of high-wage managers and professionals, among them technical managers and engineers, increased; employment shares of middle income office workers and industrial workers fall; and employment shares of low-wage retail, personal service and unskilled manual workers increased. However, the picture that emerges is more complex than this simple relationship between wage ranks

[1] The United States (Autor, Katz, and Kearney (2006), Autor, Katz, and Kearney (2008), Firpo, Fortin, and Lemieux (2011)), the United Kingdom (Goos and Manning (2007)), Germany (Spitz-Oener (2006), Dustmann, Ludsteck, and Schönberg (2007)), and more generally in Europe (Goos, Manning, and Salomons (2009) and Oesch (2013)). Polarization contrasts with earlier labor market developments, where changes in employment shares of middle-wage jobs were more modest, and the growth of high-wage jobs was at the expense of low-wage jobs. For example, in 1980s in the U.S., changes in employment shares are positively related to wages in the 1980s Autor, Katz, and Kearney (2008)).

and changes in employment shares. For example, employment in middle management declined, but technicians increased their employment shares, while both occupations earn similar middle-income wages.

The magnitudes of changes are large and they occurred relatively rapidly. Despite very different labor market institutions, polarization in France from 1994 to 2007 is comparable both in shape and in magnitude to polarization in the United States from 1980 to 2005 (Autor and Dorn (2013)).[2] This suggests that similar forces are at play. We find that polarization in France is a strong force that increases inequality through reallocation of employment shares from middle-paying occupations to both high and low-paying occupations.[3]

We decompose changes in employment shares into two components: within-firm changes and changes due to changes in firm sizes (including entry and exit). We find that these two dimensions explain varying shares of changes in employment across occupations. For example, within-firm changes explain nearly all of the overall drop in employment in skilled industrial workers, but hardly none of the drop in employment in office workers, where changes in firm sizes dominate. For the latter, it is the between-firm changes that matter, implying that employment growth in firms that are intensive in office workers lags behind other firms. We are the first to document wide dispersion across occupations in the exposure of workers to imports, exports and techies.

We then ask what factors explain employment share changes in the 12 largest occupations within firms: importing, exporting or technology? Our identification strategy allows us to make causal inferences about these forces. We find that the main driving force is technology, with trade playing a relatively minor role. Within non-manufacturing firms, technology strongly increases employment shares of top managers, while having the opposite (albeit smaller) effect on office and retail workers. Within manufacturing firms, technology causes an increase in employment shares of mid-level professionals (who are relatively high in the wage distribution), while lowering shares of foremen and supervisors (who are closer to the middle of the wage distribution) and office workers. At the same time, technology causes significant skill *downgrading* among blue collar workers.

Trade also affects the occupational mix, but mainly in manufacturing. Importing causes strong skill *upgrading*: employment shares of skilled industrial and manual laborers increase, while the

[2] See Goos, Manning, and Salomons (2014) for a comparison across European countries.

[3] This is not inconsistent with overall decreasing inequality in France, because changes in occupational wages tend to compress the overall wage distribution, as we discuss in more detail below. For example, Verdugo (2014) shows that changes in the composition of French employment across education and experience groups increase inequality in the face of overall reductions in inequality. See also Charnoz, Coudin, and Gaini (2013) for a broad view of trends in inequality in France.

share of unskilled industrial workers falls. This is consistent with a simple offshoring story, where imported intermediates substitute for low-skill workers within manufacturing firms, but are complementary to skilled workers. We find that exporting increases employment shares of top managers, lowers shares of (mid-wage) skilled industrial and manual workers, and increases shares of (low-wage) unskilled industrial workers—causing strong polarization within manufacturing. As with technology, these findings imply skill *downgrading* among blue collar workers in response to exporting.

Our results on skill downgrading within production/blue-collar occupations in response to technological change and exporting are new and intriguing, and we discuss them at length below.

Turning to between-firm changes, we find that technology has substantial effects on firms' overall employment shares: techie-intensive firms grow much faster than other firms. Importing has large effects on employment growth in manufacturing: firms that import from China and other low and middle income countries see substantially slower employment growth. This is mostly due to imports of intermediate inputs, which suggests that offshoring contributes to slower firm-level employment growth.

As the second largest economy in Europe, France is a good laboratory for studying changes in the structure of employment, where, due to its relatively rigid wage structure, shocks are more likely to affect employment rather than wages. Card, Kramarz, and Lemieux (1999) estimate similar employment responses to demand shocks across demographic groups in France, Canada and the U.S. In contrast, while wages in France are overall insensitive to demand shocks, wages do respond to demand shocks in the U.S. and Canada. These findings contribute to the external validity of our work.[4]

1.1 Literature review

Our work contributes to the literature that documents the pervasiveness of job polarization and studies its causes. Our work is distinguished by the quality of the administrative data, its comprehensiveness (the entire French private sector), and our focus on within and between firm changes.

[4] Jaimovich and Siu (2012) show that the disappearance of routine-intensive jobs in the U.S. from the 1980s coincides with "jobless recoveries". Our sample, 1994-2007, however, coincides with a relatively stable period in the French economy. Cortes, Jaimovich, Nekarda, and Siu (2014) estimate that the drop in employment in routine occupations in the U.S. is driven by changes in employment transition rates (between jobs, and between employment and non-employment), mainly among men, the young, and low skilled individuals—but not due to changes in demographic composition.

In addition, features of the French occupational classification make it particularly useful for understanding polarization, for example, by distinguishing between different skill levels within similar functions (e.g., industrial and manual labor workers). These skills are determined by employers' assessment, which makes them closer to the economic notion of "skill", rather than being determined by educational credentials.[5] The within-function skill dimension is absent in previous work on polarization.[6]

This is the first paper to describe and analyze polarization across and within firms. Since employment decisions are made by firms, firm-level data is ideal for studying polarization. Previous work exploits variation across local labor markets in the U.S. (Autor and Dorn (2013)) or across industries and countries (Michaels, Natraj, and Van Reenen (2014) and Goos, Manning, and Salomons (2014)) to identify the role of technology and globalization on polarization.[7] Only Goos, Manning, and Salomons (2014) address the role of compositional changes (industries) across these units of analysis in explaining overall polarization.

The only other paper that we know of that analyzes polarization using worker-firm data is Keller and Utar (2015). The authors analyze polarization within the Danish textile and apparel sector using matched employer-employee data. Using a sample of workers employed in the sector in 1999, their preliminary results show that the end of quota protection caused trade-exposed workers in middle-wage occupations within the textile and apparel sector to move disproportionately into higher and lower paid occupations. While not directly comparable to our economy-wide analysis, which focuses on longer term trends rather than outcomes of individual workers, the analysis of Keller and Utar (2015) is consistent with our findings. In addition—and similar to our aggregate analysis—they show that polarization in Denemark in 1991–2009 progressed much faster than in the United States in 1980–2005.

The main explanation for job polarization in the literature is the "routinization hypothesis" (Goos and Manning (2007)). As argued in Autor, Levy, and Murnane (2003), technological progress in information and communications technology (ICT) allows machines to replace codifiable cognitive

[5] These features have been exploited by others who study the French labor market, e.g. Maurin and Thesmar (2004), Maurin, Thoenig, and Thesmar (2002) and Thesmar and Thoenig (2000).

[6] A notable exception in this respect is Verhoogen (2008), who studies the effects on quality upgrading in manufacturing in Mexico, following the large 1994/1995 devaluation of the peso. He proxies worker quality by within-blue collar education levels in manufacturing.

[7] Autor, Dorn, and Hanson (2013) exploit variation in industrial composition across local labor markets and estimate significant effects of imports from China on employment and wages in U.S. manufacturing. Beaudry, Doms, and Lewis (2010) exploit variation across U.S. cities, but do not study polarization; they study changes in demand for skill (college-equivalent workers).

routine tasks that were once performed by humans. These tasks happen to be more prevalent—or "bundled"—in occupations that are, on average, in the middle of the wage distribution. Thus, the diffusion of ICT lowers demand for these occupations. At the same time, ICT complements non-routine cognitive tasks, and demand for occupations that are characterized by these tasks—which are higher up in the wage distribution—rises. Occupations at the bottom of the wage distribution are less affected by ICT, and they absorb the residual supply of labor.[8] Our results broadly support the importance of the "routinization hypothesis".

A second force that could help explain job polarization is offshoring, where domestic labor is replaced by labor abroad (see Grossman and Rossi-Hansberg (2008), Rodriguez-Clare (2010), Blinder and Krueger (2013)). Empirically, our results suggest a relatively modest role for offshoring in explaining polarization. Similarly, Feenstra and Hanson (1999) estimate that imports of intermediate inputs have a small effect on relative demand for skilled labor in U.S. manufacturing from 1979 to 1990, while computers have a large effect. Michaels, Natraj, and Van Reenen (2014) come to a similar conclusion, as does Oesch (2013).[9]

Moreno-Galbis and Sopraseuth (2014) find that population aging is an additional factor that can help explain the increase employment at the bottom of the wage distribution. Older people have relatively high demand for personal services—largely provided by low-wage workers—thus, population aging can help explain the rise of employment in low-paid positions. Another force which may operate at the bottom of the wage distribution is immigration, since this is where most immigrant find employment, at least initially; however, Oesch (2013) dismisses this as an important factor.

Another force that may be part of the explanation of changes in aggregate occupational employment shares is labor market regulation. Indeed, France experienced changes in labor market regulation during the period we study, most notably changes in regulations of the 35-hour working week. However, as Askenazy (2013) points out, the 35-hour regulations were designed to *not* to affect aggregate labor demand measured in hours worked—which is our unit of analysis—and in fact, they probably didn't. The 35-hour regulations were designed to share the existing demand

[8] Acemoglu and Autor (2011) provide an analytical framework that suggests how tasks are bundled across types of workers (differentiated by education level or skill), and how changes in demand for these tasks affect employment shares of these types.

[9] Becker and Muendler (2014) show that overall German employment in 1979–2006 shifted towards "non-offshorable" activities, while imports of intermediate inputs increase, suggesting a role for offshoring in explaining changes in labor demand. However, they do not address polarization, they do not investigate the role of technology, nor do they identify causal relationships.

across more workers, in an attempt to reduce unemployment. Even if changes in the 35-hour regulations did affect industries and occupations differently, this does not affect our identification of causal forces, as we explain below.

Our work is closely related to Maurin and Thesmar (2004), who investigate changes in employment composition within French manufacturing from 1984 to 1995. Using survey data, they find that employment in product design and marketing increases, while employment in production drops—both for high and low-skilled workers within these categories (*qualifies* and *non-qualifies*, respectively). Concurrently, employment in high-skill administrative jobs declines. Maurin and Thesmar (2004) associate these changes to technological change. Using firm level data from 1988 to 1992, Maurin, Thoenig, and Thesmar (2002) find evidence that increases in employment in product design and marketing within French manufacturing firms may be related to exporting.[10]

A key objective of our is paper is to identify causal relationships of technology and trade on firm's occupational composition and size. Our identification strategy relies on initial conditions across firms to explain changes in occupational composition and size. We use lagged values as instruments and discuss their validity in detail. This strategy is similar to that of Beaudry, Doms, and Lewis (2010) and Autor and Dorn (2013), who exploit variation across space. In contrast, Michaels, Natraj, and Van Reenen (2014) and Goos, Manning, and Salomons (2014) estimate "long differences" specifications and exploit variation across industries (and countries), but do not directly address causality.

There are also important differences between our econometric approach and those in Beaudry, Doms, and Lewis (2010) and Autor and Dorn (2013). Beaudry, Doms, and Lewis (2010) find that higher supply of college-educated workers (and commensurate low returns to college) in 1980 predicts higher rates of computer adoption and higher increases in the returns to college across U.S. cities. In contrast, Autor and Dorn (2013) find that higher levels of routine-task labor input (which is not particularly high skilled) across local labor markets in 1980 predicts higher rates of information technology adoption, job polarization and inflows of skilled labor.[11] Our approach differs from both of these. Firms that are initially more technologically-intensive in 2002 are more sensitive to reductions in the cost of computing power. Our innovative approach is to proxy

[10] Related to this, Thesmar and Thoenig (2000) use data from France from 1984 to 1995 to show that increases in product market volatility and creative destruction can lead to firm organizational change, namely substitution of product design and marketing workers for production workers.

[11] Beaudry, Doms, and Lewis (2010) use initial supply of "college equivalents", defined as workers who have a least a 4-year college degree plus one-half of those with at least some college education. If the "some college" group are predominantly employed in routine-intensive occupations in 1980, then this can help reconclie the seemingly different predictions of Autor and Dorn (2013).

technology-intensity with the share of techies in firm employment; the techie share captures the propensity to adopt technology at the firm level. Firms with a higher techie share exhibit larger changes in occupational composition and higher overall employment growth. Our approach is appropriate for our sample, which starts after information technology becomes all but ubiquitous, and while polarization is evident.

Industry level analysis masks substantial variation across firms. The importance of firms in explaining relative demand shifts is highlighted, for example, in Bernard and Jensen (1997). While Berman, Bound, and Griliches (1994) show that most (70%) of the increase in relative demand for nonproduction workers in U.S. manufacturing in the 1980s is driven by within-industry changes (versus changes in industry composition), Bernard and Jensen (1997)—using the diasaggregate data underlying the industry analysis of Berman, Bound, and Griliches (1994)—show that variation in plant sizes explains most (60%) of the increase in their wage bill share in this period. The firm level also lends itself more naturally to studying and identifying the mechanisms of adjustment.

Similar to our work, Goos, Manning, and Salomons (2014) address both compositional changes and within-unit changes in explaining polarization—but at the industry level. They also report survey data on polarization in France (their Table 2). While they are successful in explaining the contribution of changes in industrial composition to polarization, they are unsuccessful in explaining the within-industry contribution. Our work shows that for many occupations, changes in the composition of firms matter the most for understanding changes in aggregate employment shares. We discuss these findings in detail below.

Biscourp and Kramarz (2007) study the role of trade in explaining employment declines in French manufacturing from 1986 to 1992. They find that imports of final goods are associated with declines in production workers' employment, and in particular low-skill production workers' employment. In contrast, Goux and Maurin (2000) investigate the causes of the decline in low-skill employment in France form 1970 to 1993. Using survey data, they estimate that changes in industrial composition—not technological change or globalization—drive this decline.[12] These results contrast with Katz and Murphy (1992) (for the U.S., 1963–1987) and Berman, Bound, and Griliches (1994) (for U.S. manufacturing, 1979–1989), who argue that intra-industry changes are most important. Our empirical strategy identifies causal effects from within-industry variation, so we are silent on this issue.

[12] Exports and imports have offsetting effects on net, but are estimated to have some effects on gross reallocations within industries. This echoes the analysis in Harrigan and Reshef (forthcoming).

Kramarz (2008) studies the effect of offshoring on firm-level employment in French manufacturing from 1986 to 1992. He estimates that French firms that faced strong labor unions lowered employment and offshored more than firms facing weaker wage bargaining by workers. Our empirical strategy uses firm level importing activity directly. Carluccio, Fougere, and Gautier (2014) investigate the separate effects of exporting and importing on wage bargaining and the resulting wages of workers in French manufacturing from 2005 to 2009.

By studying job polarization, we also contribute to the literature on wage inequality in France. In contrast to other comparable industrial economies—e.g., the U.S., U.K., Canada and Germany—France has had relative stability in wage inequality since 1980. As Charnoz, Coudin, and Gaini (2013) and Verdugo (2014) show, the 90/10 percentile ratio falls all through our sample, and this is mostly driven by a compression in the 50/10 percentile ratio. In contrast, top wage income shares (top 1% and 0.1%) in France have increased markedly, contributing to an increase inequality, albeit less than in other countries; see Landais (2008), Amar (2010), Godechot (2012), and Piketty (2014). We estimate that polarization is a strong force that increases inequality, and that within-occupation wage compression counterbalances this.

1.2 Roadmap to the paper

Our paper has two types of empirical findings, descriptive and econometric. After describing the data in Section 2, we document the polarization of the French labor market, and how polarization has evolved both within and between firms, in Section 3. This section also introduces new measures of how workers in a given occupation are exposed to trade and to workers in different occupations. In Section 4 we present a simple model of firm-level technology which is used to motivate the econometric analysis in Section 5. The econometric analysis shows how firm characteristics in 2002 affect both within-firm polarization and between-firm employment growth from 2002 to 2007.

2 Data source description

To study job polarization in France we use firm-level data on trade and employment from 1994 to 2007. This 14 year period saw big changes in technology, globalization, and economic policy: the tech boom of the late 1990s, Chinese accession to the World Trade Organization in 2001, the introduction of the euro in 1999, and steady progress in integrating goods, financial, and labor markets within the European Union. France had center-right governments throughout the period.[13]

[13] The Socialist President Francois Mitterand left office in Spring 1995, but with the National Assembly controlled by the center-right since March 1993, the Prime Minister from 1993 to 1995 was the Gaullist Édouard Balladur.

It was also a period of macroeconomic stability in France, with no recessions (annual growth slowed to just under 1 percent in 2002 and 2003, and averaged 2.4 percent during the rest of the period). During this period, the French government implemented a set of labor market reforms intended to lower labor costs and increase employment, especially of low-skilled workers (Askenazy (2013)). This section gives an overview of our data sources, with important details about data definitions and matching of firms relegated to the data appendix.

2.1 Workers and firms: DADS *Poste*

Our source for information on workers is the DADS *Poste*, which is based on mandatory annual reports filed by all firms with employees, so our data includes all private sector French workers except the self-employed.[14] Our unit of analysis is annual hours worked in a firm, by occupation.[15] For each worker, the DADS reports gross and net wages, hours worked, occupation, tenure, gender and age. There is no information about workers' education or overall labor market experience. The data does not include worker identifiers, so we can not track workers over time, but this is of no concern to us given our focus on long-run trends rather than individual outcomes.[16] Throughout the paper, our measure of labor input is annual firm-level hours worked rather than head count. The DADS *Poste* has no information about the firm beyond the firm identifier and industry and, implicitly, firm-level aggregates related to employment such as total hours worked by occupation, average wages, etc.

2.2 Occupations: the PCS

Every job in the DADS is categorized by a two digit PCS occupation code.[17] Excluding agricultural and public sector categories, the PCS has 22 occupational categories, listed in Table 1.[18] These 22 categories are consistently defined over our period of analysis.[19] In much of our analysis we focus on the 14 larger PCS categories indicated in bold in Table 1, each of which comprises between 2 percent and 13 percent of private sector hours worked, and which together comprise 95 percent of hours worked.

[14] The DADS *Poste* is an INSEE database compiled from the mandatory firm-level DADS ("Déclaration Annuelle de Données Sociales") reports.

[15] The data is reported at the level of establishments, which are identified by their SIRET. The first nine digits of each SIRET is the firm-level SIREN, which makes it easy to aggregate across establishments for each firm.

[16] The DADS *Panel* is a related dataset which has been used by researchers interested in following individuals over time (for example, Abowd, Kramarz, and Margolis (1999) and Postel-Vinay and Robin (2006)). The DADS *Panel* is a 1/25 sample of individuals in the DADS Poste.

[17] PCS stands for "Professions et Catégories Socioprofessionnelles".

[18] We also exclude a very small category first introduced in 2002, PCS 31, and allocate these workers to PCS 34.

[19] There are some small discontinuities in how workers are assigned to occupations between 2001 and 2002. See the appendix for a description of how we cope with this isssue.

Each two digit PCS category is an aggregate of as many as 40 four digit subcategories. Although hours worked data is not available by four digit category, the descriptions of the four digit categories in Table 2 are helpful in understanding the kinds of tasks performed within two-digit categories, and make it clear that the two-digit categories are economically meaningful. The subcategories also suggest differences in the susceptibility of jobs to automation and/or offshoring. For example, Personal Service workers (PCS 56) such as restaurant servers, hair stylists, and child care providers do the sort of "routine manual" tasks (c.f. Autor, Levy, and Murnane (2003)) that require both proximity and human interaction. The same can be said for Retail Workers (PCS 55) and both skilled and unskilled manual laborers (PCS 63 and 68), whose jobs include gardening, cooking, repair, building trades, and cleaning. By contrast, mid-level professionals and managers (PCS 46) often do routine cognitive tasks that can be done more cheaply by computers or overseas workers. Industrial workers (PCS 62 and 67) doing routine manual work are unquestionably directly in competition with both robots and imported intermediate goods. Drivers (PCS 65) do a job which can be neither offshored nor automated (at least for now), while the work of skilled transport/wholesale/logistics workers (PCS 65) is likely subject to automation.

Two occupations are of particular interest: PCS 38 "Technical managers and engineers" and PCS 47 "Technicians". As is clear from the detailed descriptions in Table 2, workers in these categories are closely connected with the installation, management, maintenance, and support of information and communications technology (ICT). We refer to workers in these two occupations as "techies". Our hypothesis is that techies mediate the effects of new technology within firms: they are the ones who plan, purchase, and install new ICT equipment, and who train and support other workers in the use of ICT. In short, if a firm invests in ICT, it needs techies, and firms with more techies are probably more technologically sophisticated firms.

One potential problem with our hypothesis that firm-level techies are an indicator of firm-level technological sophistication is that firms can purchase ICT consulting services. By hiring a consultant, firms can obtain and service new ICT without hiring a large, permanent staff of techies. However, only 0.7% of techie hours worked are in the IT consulting sector, which implies that more than 99% of the hourly services supplied by techies are obtained in-house rather than from consultants.[20]

[20] What we refer to as the IT consulting sector is industry code 72 in the NAF classification, which includes the following sub-categories: Hardware consultancy, Publishing of software, Other software consultancy and supply, Data processing, Database activities, Maintenance and repair of office, Accounting and computing machinery, and Other computer related activities.

2.3 Matched firm-trade

Our source for firm-level trade data is the French Customs. For each trade observation, we know the importing or exporting firm, trading partner country, the product traded, and the value of trade. We use the firm-level SIREN identifier to match the trade data to the DADS Poste data on employment. This match is not perfect: we fail to match about 11 percent of imports and exports to firms. The reason for the imperfect match is that there are SIRENs in the trade data for which there is no corresponding SIREN in the DADS Poste. This is likely to lead to a particular type of measurement error: for some firms, we will observe zero trade even when true trade is positive.

3 Descriptive results

In this section we do five things:

1. Show how the French job market polarized between 1994 and 2007, both within and between firms.
2. Illustrate the *March of the Techies*: the growing importance of occupations that specialize in new technology.
3. Calculate the extent to which polarization has been a force that increases wage inequality.
4. Introduce a new measure of an occupation's exposure to trade.
5. Characterize the extent to which employees in different occupations work in the same firm.

Our basic unit of observation is hours worked in a firm, classified by occupation. We report various aggregates of this data, using the following notation:

h_{fot}	hours worked in firm f by occupation o in year t.
$h_{ft} = \sum_o h_{fot}$	hours worked in firm f in year t, across all occupations o.
$s_{fot} = \frac{h_{fot}}{h_{ft}}$	share of occupation o hours in firm f hours, year t.
$H_{ot} = \sum_f h_{fot}$	aggregate hours worked in occupation o in year t.
$\lambda_{ft} = \frac{h_{ft}}{\sum_f h_{ft}}$	share of firm f in aggregate hours worked in year t.
$S_{ot} = \sum_f \lambda_{ft} s_{fot}$	share of occupation o hours in aggregate hours worked in year t.

From 1994 to 2007, 16.7 million private sector firms appear in our DADS Poste data.[21] These firms range in size from tiny cafes and *tabacs* to giant industrial enterprises and retailers. Most of our descriptive analysis includes all 16.7 million firms, but in our econometric analysis we focus on the subset of firms that were in operation continuously from 1994 to 2007. There are 310,713 of these "permanent" firms, with 85% of hours worked in non-manufacturing. Though these firms represent less than 2 percent of firms in our sample, they are much larger than the average firm, and account for about half of aggregate hours worked in each year.

3.1 Occupational polarization and the *March of the Techies*

In this section we present the first major results of our paper: the French occupational structure polarized between 1994 and 2007, with high-wage and low-wage occupations growing at the expense of middle-wage occupations. To show this, we begin with Figure 2, which plots economy-wide occupational hours shares S_{ot} from 1994 to 2007, separately for manufacturing and nonmanufacturing (for readability, the scales are different for each occupation). The share of hours worked by upper and technical managers, along with technicians, saw steady growth, while the share worked by middle managers and foremen-supervisors fell. The largest occupation in 1994, office workers, fell steadily, while retail and personal service jobs grew. Among industrial workers in manufacturing, there was substantial skill upgrading, with the share of hours accounted for by high skilled workers rising as the share of low skilled workers declined.

Particularly striking in Figure 2 is the rapid growth in the techie occupations, Technical Managers and Engineers (PCS 37) and Technicians (PCS 47). While techies have a larger hours share in manufacturing, they also have a large and growing presence in nonmanufacturing, especially Technical Managers. We call this growth in the importance of these two occupations *The March of the Techies*.

We next connect changes in occupational shares to average occupational wages. Polarization is illustrated vividly in Figure 3, which plots the change in an occupation's share of aggregate hours from 1994 to 2007 against the occupation's rank in the wage distribution in 2002.[22][23] The circles are proportional to the average size of occupations, and the curve is a weighted quadratic regression line. The pattern is clear: the two large, highly-paid occupations on the right, PCS 37 (Managers)

[21] SIRENs in the DADS Poste are classified by *categorie juridique*. We define private firms as those with SIRENs other than *categorie juridique* 4, 7, or 9. There are 3.6 million other SIRENs in the DADS Poste, including public sector enterprises and nonprofits.

[22] This ranking is stable over time, and insensitive to defining wages as gross or net of payroll taxes.

[23] Autor and Dorn (2013) use a similar figure to illustrate job polarization in the United States from 1980 to 2005 (their Figure 1, Panel A).

and PCS 38 (Technical Managers) grew, as did three large low-wage occupations on the left: PCS 68 (Low-skilled manual laborers), PCS 56 (Personal service workers), and PCS 55 (Retail workers). The middle-wage occupations that shrank over the period include skilled industrial workers and manual laborers (PCS 62 and 63), unskilled industrial workers (PCS 67), and clerical and middle-management workers (PCS 54 and 46). Exceptions to this pattern in the middle of the wage distribution include drivers (PCS 64), an occupation that can be neither offshored nor automated, and Technicians (PCS 47). To summarize, polarization and the march of the techies proceeded together from 1994 to 2007.

Theses changes are large and occurred relatively rapidly. Polarization in France in from 1994 to 2007 is comparable both in shape and in magnitude to polarization in the United States from 1980 to 2005 (Autor and Dorn (2013)), a period almost twice as long.[24]

Figures 4 for nonmanufacturing and 5 for manufacturing firms offer a useful refinement of the economy-wide story seen in Figure 3. Figure 4 shows the different fortunes of office workers (PCS 54), whose hours share plummeted, and of the lower-paid service sector occupations, retail and personal service workers (PCS 55 and 56), whose ranks swelled considerably. There was skill downgrading within manual workers (PCS 63 fell while 68 grew).

As seen in Figure 5, a simple polarization story does not describe what happened within manufacturing. Instead, the key fact is skill upgrading among blue-collar industrial workers: the hours share of the skilled (PCS 62) grew at the same time that the share for unskilled workers (PCS 67) plunged. As in nonmanufacturing, the managerial categories (PCS 37 and 38) grew strongly while office workers and middle managers (PCS 54 and 46) lost ground.

To better understand the patterns just illustrated, we turn next to a more detailed analysis of the changes in hours shares: how big were these dramatic changes, and did they occur between firms, within firms, or both? The aggregate share of hours worked in occupation o in the economy S_{ot} can be written as

$$S_{ot} = \sum_f \lambda_{ft} s_{fot}$$

[24] To see this, notice that the scale of Panel A of Figure 1 in Autor and Dorn (2013) is "100 $\times$ change in employment share", and each observation is for one percentile. In contrast, we have 22 occupations. This means that each 0.1 unit in their figure translates to $0.45 = 0.1/100 \times (100/22) \times 100$ percent points, on average, in our figures. See Goos, Manning, and Salomons (2014) for a comparison across European countries.

where λ_{ft} is firm f's share of total hours and s_{fot} is occupation o's share of hours in firm f. The change in S_{ot} can be decomposed into changes in the size of firms with different s_{fot} and changes in s_{fot} within firms as follows:

$$\Delta S_{ot} = \underbrace{\sum_f \Delta\lambda_{ft}\overline{s}_{fo}}_{between} + \underbrace{\sum_f \overline{\lambda}_f \Delta s_{fot}}_{within} \tag{1}$$

where overbars indicate simple time averages. Entry and exit of firms is accounted for by changes in the λ_{ft} from zero to positive or from positive to zero. Our between-within results are reported in Table 3 for the whole period and the entire private sector. The fourteen largest occupations are boxed in Table 3 and illustrated in Figure 6.

Begin by looking at the full period for all firms, which is illustrated in Figure 6 and reported in the first four columns of Table 3. The top managerial categories both grew a lot, but technical managers (PCS 38, +2.0pp) grew much faster than upper managers (PCS 37, +1.4pp). Middle manager (PCS 46, -1.5pp) and supervisor (PCS 48, -0.4pp) jobs shrank, but similarly-paid technician jobs (PCS 47, +1.0pp) grew substantially. Turning to the lower paid occupations, we see substantial polarization and evidence consistent with the decline of jobs vulnerable to automation and offshoring. Among the white collar occupations, office jobs (PCS 54, -2.0pp) plunged while lower paid retail (PCS 55, +1.5pp) and personal service (PCS 56, +1.2) jobs grew. Among blue collar occupations, the picture is more nuanced: high skill industrial (PCS 62, -1.0pp) and manual labor (PCS 63, -0.3pp) jobs fell, but similarly skilled and paid jobs in driving (PCS 64, +0.7pp) and distribution (PCS 65, +0.2pp) grew. At the bottom of the skill ladder, relatively well-paid industrial jobs (PCS 67, -3.0pp) plunged while the lowest paid occupation in the economy (low skilled manual labor, PCS 68, +0.4) grew.

The between-within decompositions help us understand these changes in greater depth. Focus first on the fortunes of high and low skill industrial workers, PCS 62 and PCS 67, both of whom saw big overall declines. For the high-skill industrial workers in PCS 62, the overall decline of -1.0pp was more than entirely due to within-firm changes: firms that had above average amounts of these workers actually contributed +0.2pp to hours growth, but within firm shedding of these workers contributed a -1.2pp drop. The story is exactly the opposite for the low skill industrial workers in PCS 67: the overall collapse of -3.0pp was driven by a -3.4 drop due to between-firm changes, with jobs actually being added within firms, +0.4pp. Putting these two facts together gives a clear picture: firms intensive in skilled industrial workers grew, but within these firms there was substitution of unskilled for skilled industrial workers.

Next, consider the skilled and unskilled manual labor occupations, PCS 63 and PCS 68. As discussed above, these jobs are probably less subject to both automation and offshoring than the similarly skilled, but better paid, industrial jobs. Firms that were intensive in these occupations shrank, contributing -1.3pp and -0.4pp to the overall declines in PCS 63 and PCS 68 respectively. But within firms the importance of these jobs actually increased substantially, by 1.0pp and 0.8pp respectively. In other words, even as these manual-labor-intensive firms shrank, they did so by shedding other workers faster than their manual laborers.

Drivers, PCS 64, are the archetypal low-skill job that can not be automated (at least for now) or offshored. Thus, it is not surprising that their hours share grew +0.7pp, even as other blue-collar jobs were shrinking. This was driven by within-firm changes, +1.1pp, that were partly offset by a between-firm decline in firms that use a lot of drivers, -0.4pp.

Turning to clerical workers, PCS 54, the -2.0pp collapse in office jobs was more than accounted for by the between-firm component: firms that had a lot of office workers shrank substantially, contributing -2.4pp to the overall decline, even as the within-firm component was +0.4. This within-between split is not consistent with a simple story of replacing clerical workers with computers; rather, it is suggestive of a heavy reliance on office workers being associated with slower firm employment growth. This finding suggests that models that rely on substitution—either within local labor markets or industries—are missing an important dimension of the mechanics of polarization.

The accompanying boom in lower-paid retail (PCS 55, +1.5pp) and personal service (PCS 56, +1.2pp) jobs was fairly evenly split across the within and between components. Thus, firms heavy in retail and/or personal service jobs expanded, and increased the share of these jobs within their firms as they did so.

The march of the techies was broad based. Both technical managers (PCS 38, +2.0pp) and technicians (PCS 47, +1pp) grew rapidly. This growth was mainly accounted for by between-firm changes (techie-intensive firms grew faster, accounting for more than 75% of total techie hours growth), but in addition firms on average shifted hours toward techies.

3.2 Contribution of polarization to inequality

How much does job polarization contribute to wage inequality? Reallocation of labor from middle-paying occupations to both high and low-paying occupations will increase inequality, and here we calculate how much.

We measure wage inequality across occupations in year t by the weighted standard deviation of relative occupational wages:

$$\sqrt{\frac{1}{21}\sum_{o} S_{ot}\left(\omega_{ot}-\overline{\omega}_{t}\right)^{2}}, \tag{2}$$

where S_{ot} is the hours share of occupation o, ω_{ot} is the average wage of occupation o, and $\overline{\omega}_t$ is the overall weighted average wage. This measure is equivalent to the weighted coefficient of variation, and has the virtue of being scale independent, and thus invariant to general trends in nominal wages (see Cowell (2008)).[25]

Occupational inequality as measured by (2) rose a modest 6 percent from 0.1033 in 1994 to 0.1095 in 2007. Changes in our occupational inequality measure (2) embody two opposing forces: changes in average occupational wages and in the shares of occupations in the economy. To isolate the impact of polarization (compositional changes in occupational employment shares) on this measure of inequality, we proceed in two ways. The first is to fix wages in 1994 and let employment shares evolve as in the data. We find that polarization contributed 143% of the actual increase in occupational inequality from 1994 to 2007. In the second calculation we fix employment shares in 1994 and let relative wages evolve as in the data. We find that changes in occupational wages contribute -14% of the actual increase in σ from 1994 to 2007, and implies that polarization contributed 114% of the change.[26] Both calculations imply that polarization has strongly increased inequality, whereas compression of the distribution of wages across broad occupations has worked to reduce inequality. This result—between-occupation wage compression with reallocation of hours across occupations that increases overall wage inequality—is consistent with findings in Charnoz, Coudin, and Gaini (2013) and Verdugo (2014).

3.3 Trade exposure of occupations

A key question in understanding job polarization is: how exposed are workers to the forces that are potentially driving polarization? Because we have data that matches firms and trade, we can construct measures of firm-level exposure of different occupations to imports and exports - measures which have not been calculated before in the literature. To construct these measures, we allocate firm-level exports x_{ft} to workers within the firm, by occupation, and then sum across firms to get economy-wide measures of occupational export exposure,

[25] We splice the ω_{ot} series between 2001 and 2002 using the same methodology that we use to splice the S_{ot} series, as described in the Appendix.

[26] These results are obtained when splicing employment and wage bill shares, and taking their ratio to obtain relative wages. When splicing employment shares and relative wages, the contribution of polarization is slightly larger: 153% and 124%, respectively. See appendix for complete details.

$$X_{ot} = \sum_f x_{ft} s_{fot}, \tag{3}$$

where s_{fot} is defined, as above, as the share of occupation o hours in firm f hours worked in year t. We then divide X_{ot} by aggregate exports X_t to give the share of aggregate exports allocated to occupation o. We define M_{ot}, imports allocated to occupation o, similarly. The scale of the occupational trade shares are not particularly meaningful, so we report occupational trade shares relative to the occupation's share of aggregate hours S_{ot}, with the ratios averaged over time.[27] Thus, in Figure 7, workers in occupations with exposure greater than one are more exposed than the average worker to trade.

Figure 7 shows great variation in exposure to trade by occupation. Import and export exposure are correlated, which reflects the well-known fact (see for example Bernard, Jensen, Redding, and Schott (2007)) that firms that trade tend to both import and export. The most trade-exposed occupations are Upper Managers (PCS 37) and Techies (PCS 38 and 47). Highly skilled industrial workers (PCS 62) are very exposed to trade, particularly to exports, and the same is true for Supervisors (PCS 48). What this means is that these workers are concentrated in firms which export and, to a lesser extent, import. Interestingly, the less-skilled industrial workers (PCS 67) are only slightly more exposed to exports, and no more exposed to imports, than the average worker.

By contrast, manual laborers (PCS 63 and 68), retail workers (PCS 55), drivers (PCS 64), and especially personal service workers (PCS 56) are comparatively unexposed to trade. To a lesser extent the same is true for office workers (PCS 54), the largest occupation in the economy.

There are two important caveats in interpreting these numbers. First, the trade exposure indices treat all workers in a firm as equally exposed to the firm's trade. Second, the indices reflect only direct firm-level exposure to trade, and do not account for any exposure to trade that comes through competition in product markets. We address the causal effects of firm-level trade exposure in our econometric analysis below.

3.4 Techie exposure of occupations

Our working hypothesis is that techies are the key channel that translate falling ICT prices into changes in the firm level occupation mix. An implication is that firms with more techies may

[27] There is very little time series variation in relative occupational exposure to trade, so we report the time-averages for simplicity.

see greater ICT-enabled changes in occupational mix. As a step toward measuring this effect, in this section we introduce measures of occupational exposure: what share of workers overall, and by occupation, work in firms with techies? The answer is that more than half of all workers are exposed to techies, and that exposure to techies varies a lot across occupations. We also report exposure of workers to other occupations.

To begin, we compute the share of hours worked that occur in firms that employ occupation o. This measure of overall exposure to occupation o is given by

$$\frac{\sum_f d_{oft} h_{ft}}{\sum_f h_{ft}}$$

where d_{oft} is an indicator equal to 1 if firm f has at least one hour worked by occupation o in year t. This share includes exposure of occupation o workers to themselves, so we also compute a measure that excludes this own-exposure,

$$\frac{\sum_f d_{oft} \left(h_{ft} - h_{oft}\right)}{\sum_f h_{ft}}$$

To get a clearer picture of how occupations interact at the firm level, we also compute occupation-by-occupation exposure,

$$\frac{\sum_f d_{oft} h_{o'ft}}{\sum_f h_{o'ft}}$$

The result of computing occupation-by-occupation exposure is a non-symmetric square matrix, where each row gives the exposure of occupation o' to all of the occupations o. The diagonal elements are 1 by definition, while the off-diagonal elements answer the question: what share of hours in occupation o' are worked in firms that also employ occupation o?

The occupational exposure measures do not change much over time, so we report results for a single year, 2002, in Table 4. The first two rows report overall exposure, excluding and including an occupations' exposure to itself. Focusing on the column for PCS 38, technical managers and engineers, the Table shows that 55 percent of hours worked in the economy were in firms that also had hours in this techie occupation (the number rises to 60 percent including PCS 38 exposure to itself). The corresponding number for PCS 47, technicians, is 56 percent. Moving down the column labeled 38, we see great heterogeneity in exposure to technical managers: 77 percent for top managers (PCS 37), and only 21 percent for personal service workers (PCS 56). The highest exposure is for skilled industrial workers (PCS 62, 83 percent), with very high exposure for other low-skilled industrial workers as well (PCS 67, 77 percent). The biggest occupation in the economy, office workers (PCS 54), is less exposed than average to technical managers, with just over half of office workers sharing a firm with a technical manager. Not surprisingly, the two techie occupations are very highly exposed to each other, at 86 percent for both. Other occupations' exposure to the two techie occupations is quite similar (to see this, compare the columns labeled 38 and 47).

4 Techies and Polarization: an illustration

The heterogeneity across occupations of exposure to techies shown in Table 4 is further motivation for our hypothesis that techies are a channel through which falling ICT prices cause polarization. In this section we show this channel theoretically, with a simple model of firm-level outcomes. The model shows how a drop in the price of ICT can lead to polarization of employment within a firm, and shows how polarization depends on parameters of the firm's technology. These results help to motivate our within- and between-firm econometric analyses in the following sections. Proofs of all statements are in the appendix.

4.1 Technology

We begin with a constant returns to scale production function which combines three types of non-techie labor services, along with ICT, into output Q:

$$Q = \left(\frac{L}{1-\alpha-\beta}\right)^{1-\alpha-\beta} \left(\frac{\widetilde{M}}{\alpha}\right)^{\alpha} \left(\frac{\widetilde{H}}{\beta}\right)^{\beta}$$

In this function, L is simply hours worked by low-skill workers. The other components of the production function combine hours worked by medium- and high-skill workers, M and H, with ICT services $\widetilde{C}$,

$$\widetilde{M} = \left[\theta^{\frac{1}{\eta}} \widetilde{C}^{\frac{\eta-1}{\eta}} + (1-\theta)^{\frac{1}{\eta}} M^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}$$

$$\widetilde{H} = \left[\theta^{\frac{1}{\sigma}} \widetilde{C}^{\frac{\sigma-1}{\sigma}} + (1-\theta)^{\frac{1}{\sigma}} H^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

$\widetilde{M}$ is an aggregate of the tasks performed by medium-skill workers together with ICT services, and $\widetilde{H}$ is similarly an aggregate of tasks produced by high-skill workers together with ICT services. Our assumption that ICT is a substitute for M and a complement to H is given by $\eta > 1$ and $0 < \sigma < 1$. θ is a parameter that indexes the importance of ICT in production.

ICT technology does not affect production unless it is installed, maintained, and managed by technicians and managers with the appropriate education, training, and experience. To express this idea in the simplest way possible, we specify ICT services $\widetilde{C}$ as a Leontief function of "techies" T and ICT capital K,

$$\widetilde{C} = \min[T, K]$$

The three types of workers are paid w_L, w_M, and w_H. Techies are paid w_T, and ICT capital is paid a rental rate of r. The unit cost function corresponding to this technology is

$$b = w_L^{1-\alpha-\beta}\widetilde{p}_M^{\alpha}\widetilde{p}_H^{\beta}$$

where the price indices of medium- and high-skill tasks are

$$\widetilde{p}_M = \left[\theta p_C^{1-\eta} + (1-\theta)\, w_M^{1-\eta}\right]^{\frac{1}{1-\eta}}$$

$$\widetilde{p}_H = \left[\theta p_C^{1-\sigma} + (1-\theta)\, w_H^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$$

and the price of ICT services is

$$p_C = w_T + r$$

Using Shepard's Lemma, the relative employment levels of workers are

$$\frac{H}{L} = \frac{\beta}{1-\alpha-\beta}\left(\frac{(1-\theta)\, p_C^{\sigma-1} w_L}{\theta w_H^{\sigma} + (1-\theta)\, p_C^{\sigma-1} w_H}\right)$$

$$\frac{M}{L} = \frac{\alpha}{1-\alpha-\beta}\left(\frac{(1-\theta)\, p_C^{\eta-1} w_L}{\theta w_M^{\eta} + (1-\theta)\, p_C^{\eta-1} w_M}\right)$$

$$\frac{H}{M} = \frac{\beta}{\alpha} p_C^{\sigma-\eta}\left(\frac{\theta w_M^{\eta} + (1-\theta)\, p_C^{\eta-1} w_M}{\theta w_H^{\sigma} + (1-\theta)\, p_C^{\sigma-1} w_H}\right)$$

4.2 Cross-sectional variation in relative employment

A key parameter in the technology just described is θ, the distributional parameter associated with ICT services in the functions $\widetilde{H}$ and $\widetilde{M}$ that create high- and medium-skill tasks (the share of ICT services in total cost is increasing in θ). How does cross-sectional variation in θ affect the composition of employment within firms? We answer this question by differentiating the relative employment equations with respect to θ, which gives

$$\frac{\partial}{\partial\theta}\left(\frac{H}{L}\right) < 0$$

$$\frac{\partial}{\partial\theta}\left(\frac{M}{L}\right) < 0$$

For both H and M, higher θ is associated with lower employment relative to L. The reason is that as the importance of ICT in producing high- and medium-skill tasks rises, the labor that is required to work with ICT capital falls. Since there is no direct effect of θ on the productivity of L, the ratios H/L and M/L decline with θ. The effect of θ on H/M cannot be signed.

4.3 Polarization with falling ICT prices

We next turn to the effect of falling ICT prices on relative employment within firms. A drop in r leads to a polarization in employment, with H rising relative to M and L, and M falling relative to H and L,

$$\frac{\partial}{\partial r}\left(\frac{H}{L}\right) < 0$$
$$\frac{\partial}{\partial r}\left(\frac{M}{L}\right) > 0$$

$$\frac{\partial}{\partial r}\left(\frac{H}{M}\right) < 0$$

The intuition is straightforward: since ICT is a complement to H but a substitute for M, a drop in r leads to greater employment of H and less of M.

We now turn to a key question which helps motivate our empirical specification below: is the polarizing effect of falling r stronger within firms where ICT is more important? Mathematically, is the cross derivative $\frac{\partial^2}{\partial r \partial\theta}\left(\frac{H}{M}\right)$ negative? Intuition suggests yes, and we show in the appendix that $\frac{\partial^2}{\partial r \partial\theta}\left(\frac{H}{M}\right)$ is negative for most of the relevant regions of the parameter space.

We illustrate the forces at work with a numerical example. In the example we normalize the wage of the least skilled workers to 1, and set $w_M = 2$ and $w_H = 3$. The elasticities of substitution are $\eta = 2$ and $\sigma = 1/2$, and the upper-level cost shares α, β are equalized at $1/3$. We drop the cost of ICT services p_C from 11 to 1, and analyze how the resulting ratio H/M varies as a function of $\theta \in [0, 1]$. The figure below, a contour plot of the level of H/M, illustrates what we find. The vertical axis measures the cost of computer capital r, while the horizontal axis measures the parameter θ. Lower levels of H/M are at the upper right of the figure, shaded blue, with higher levels of H/M shading toward orange. Moving from the top to the bottom of the figure illustrates our analytical result that a drop in r leads to an increase in H/M, as ICT services complement H and substitute for M. This increase is steeper for higher levels of θ: the more important ICT is in

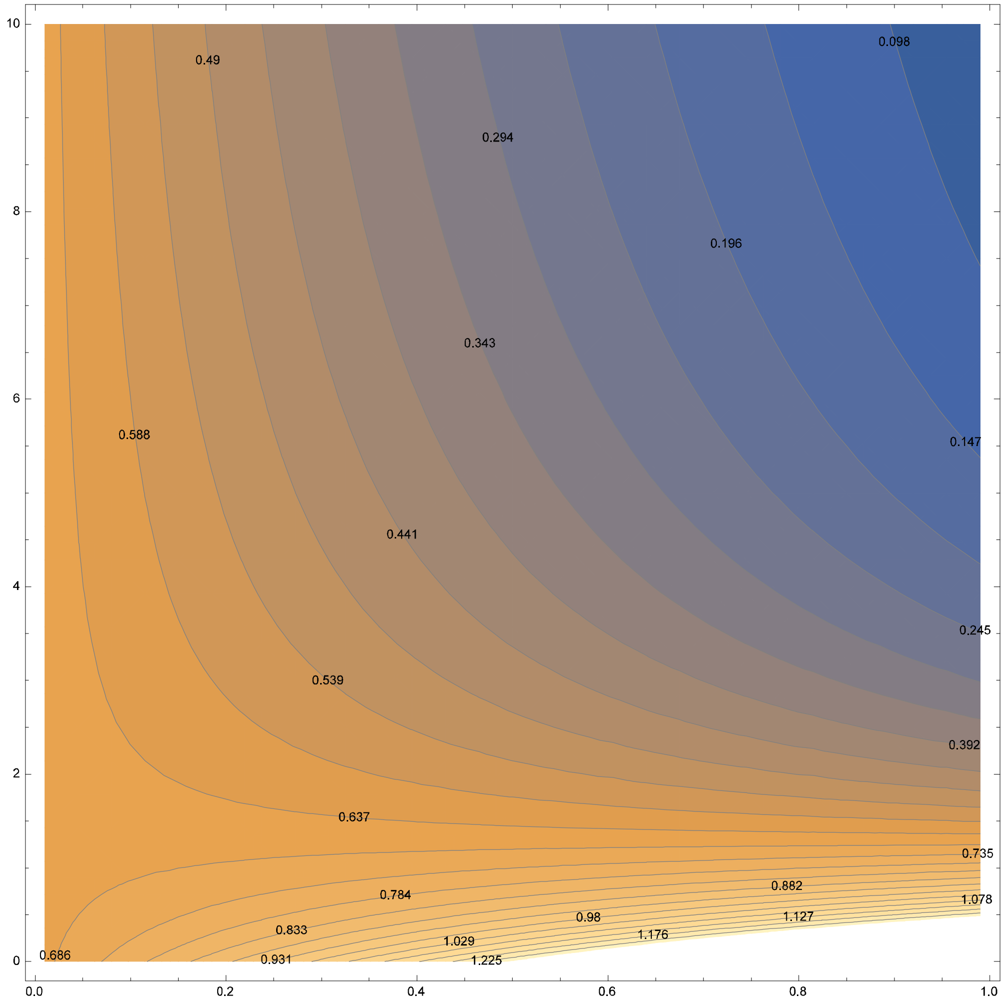

Figure 1: H/M as a function of r and θ

the production function, the greater the polarizing effect of a drop in r (to see this, note that when more contour lines are crossed for the same vertical drop, then the level of the function is changing faster). The figure also shows that the effect of higher θ on H/M is ambiguous: for low levels of r (at the bottom of the figure), higher θ is associated with higher H/M, but for higher values of r the effect is reversed.

4.4 Techies and competitiveness

We now turn to discussing the between-firm effect of falling computer prices. While a drop in the price of computers r benefits all firms that employ ICT services by lowering their unit costs b

($\partial b/\partial r > 0$ when $\theta > 0$), firms that are more ICT-intensive (higher θ) benefit more:

$$\frac{\partial^2 b}{\partial r \partial \theta} > 0 \ .$$

This means that, following a drop in r, ICT-intensive firms become relatively more cost competitive, and under any plausible demand system this will lead to market-share gains for ICT-intensive firms.

There are three effects of falling r on the total demand for labor in high-θ firms relative to low-θ firms. The first is the just-mentioned competitiveness effect, which will raise the relative output of high-θ firms. The second effect is the substitution effect of ICT for medium-skilled labor M, and the third is the complementary effect of ICT on high-skilled labor H. The net effect on total employment of the substitution and complementarity effects is ambiguous, so the effect of ICT-intensity on employment growth is an empirical matter, which we investigate in Section 6 below.

To summarize, a fall in r will lead to an increase in aggregate demand for H relative to M through a within-firm channel, and possibly through a between-firm channel. The within-firm effect is due to substitution of H for M within firms, and the between-firm effect is due to the increasing competitiveness of high-θ firms.

5 Econometric analysis of within firm changes in occupational structure

The broad research question of this section is: what explains changes in the occupational structure of French firms, and in particular the job polarization that was documented above? Our hypothesis is that both globalization and technological change are important causal factors, and the purpose of our econometric analysis is to quantify their importance. We measure changes in a firm's occupational structure by changes in the share of hours worked in one of twelve PCS occupations, excluding the share of techies (PCS 38 and 47). Changes in this "ex-techie" share are explained by firm-level measures of exposure to globalization (imports and exports as a share of the firm's wage bill) and technology (the share of techies in hours worked).

5.1 Estimating equations

In this section we specify an econometric model of the occupational composition of firms. Given our research question, the firm-occupation outcome measure of interest is the ex-techie share of hours worked. In what follows we motivate an instrumental variable regression strategy that identifies the causal effect of techie and trade exposure on within-firm changes in the twelve large non-techie occupations listed in Table 2.

We begin with a very general specification for the determinants of s_{fot}, the level of the ex-techie employment share of occupation o in firm f at time t. We allow s_{fot} to depend linearly on a time-invariant firm fixed effect β_f^o, a firm-specific time trend D_f^o, time-varying firm characteristics x_{kft}, and an error term ε_{fot},

$$s_{fot} = \beta_f^o + D_f^o \cdot t + \sum_k \beta_k^o x_{kft} + \varepsilon_{fot} \ , \tag{4}$$

The list of firm characteristics x_{kft} includes techies and trade indicators, as well as other firm characteristics which we can not measure, such as capital and intermediate inputs. We think of this equation as being the outcome of the firm's dynamic cost minimization problem. We estimate (4) in first differences from $t-1$ to t

$$\Delta s_{fot} = D_f^o + \sum_k \beta_k^o \Delta x_{kft} + \Delta\varepsilon_{ft}^o = D_f^o + u_{ft}^o \ .$$

Here $u_{ft}^o = \sum_k \beta_k^o \Delta x_{kft} + \Delta\varepsilon_{ft}^o$ is a composite term that includes changes in the firm characteristics x_{kft}'s and changes in the error term ε_{fot}.

We model the firm-specific time trend D_f^o as a function of the *level* of techies and trade in time $t-1$. Firms that do not trade at all, and/or that that have no techies at all, are likely to be distinctly different from firms that do trade and/or have techies, so to accommodate this we allow techies and trade to enter D_f^o non-linearly. Finally, we allow D_f^o to depend on an industry i fixed effect β_i^o.[28] Let $techies_{t-1}$ be the share of techies in period $t-1$ hours worked and $techpos_{t-1}$ be an indicator equal to one if $techies_{t-1} > 0$, and similarly for imports and exports (both divided by the total gross wage bill of the firm). For each occupation o, the equation to be estimated is then

$$\begin{aligned}\Delta s_{fot} \quad = \quad & \beta_i^o + \beta_1^o techies_{ft-1} + \beta_2^o techpos_{ft-1} \\ & + \beta_3^o exports_{ft-1} + \beta_4^o exppos_{ft-1} \\ & + \beta_5^o imports_{ft-1} + \beta_6^o imppos_{ft-1} + u_{ft}^o\end{aligned}$$

or, more compactly,

[28] To be precise, we define an indicator function equal to 1 if firm f is in industry i. The parameter β_i^o is the coefficient that multiplies this indicator.

$$\Delta s_{fot} = \beta_i^o + \boldsymbol{\beta}^o \mathbf{X}_{ft-1} + u_{ft}^o \ . \tag{5}$$

The rationale for this specification is that there are industry and/or economy-wide trends in ICT prices and globalization that will affect changes in firms' occupational mix through firms' initial levels of techies and trade. For example, a firm with a large techie share will be more directly affected by falling IT prices than a firm that has few techies, as in the model of Section 4 above. Similarly, a firm that exports final goods or purchases imported inputs will be more affected by the increased integration of Eastern Europe, China, and India into the world economy than will a firm that does not trade. Thus, equation (5) allows us to estimate the heterogeneous effect of aggregate trends on firm outcomes, where the heterogeneity is captured by firm characteristics in the initial period. With industry fixed effects β_i^o, the six parameters of interest $\{\beta_1^o, ..., \beta_6^o\}$ are identified by variation across firms within industries in the levels of techies and trade and by changes in the ex-techie share. Industry and occupation-specific factors that may affect firm-level labor demand are controlled for by the industry and occupation-specific fixed effects, β_i^o.[29]

The specification in (5) has the feature that the marginal effects of techies and trade are constant. This is potentially restrictive, since (for example) the effect of techies might depend on whether or not a firm trades. To allow for this possibility, we also estimate a specification where the effects of techies are interacted with the trade variables,

$$\begin{aligned}
\Delta s_{fot} \quad = \quad & \beta_i^o + \beta_1^o techies_{ft-1} + \beta_2^o techpos_{ft-1} \\
& + \beta_3^o exports_{ft-1} + \beta_4^o exppos_{ft-1} + \beta_5^o imports_{ft-1} + \beta_6^o imppos_{ft-1} \\
& + \left(\beta_7^o exports_{ft-1} + \beta_8^o exppos_{ft-1} + \beta_9^o imports_{ft-1} + \beta_{10}^o imppos_{ft-1}\right) \times techies_{ft-1} \\
& + \left(\beta_{11}^o exports_{ft-1} + \beta_{12}^o exppos_{ft-1} + \beta_{13}^o imports_{ft-1} + \beta_{140}^o imppos_{ft-1}\right) \times techpos_{ft-1} \\
& + u_{ft}^o
\end{aligned} \tag{6}$$

Our estimating equations are similar to models estimated by Autor and Dorn (2013) and Beaudry, Doms, and Lewis (2010). In Beaudry et al., the authors show that city-level variation in the adoption of PC technology is caused by predetermined city-level differences in the abundance of highly educated labor. Similarly, Autor and Dorn (2013) show that labor markets with higher levels of "routineness" see larger increases in low-wage service employment. Both of these papers

[29] For example, Askenazy (2013) describes how some occupations were differentially affected by the 35-hour regulations. This does not affect our causal inference, although it could potentially be part of what we measure at the aggregate level.

use lagged levels as instruments for levels in the 1980s. A contribution of our approach is that we locate the effects of technology adoption in firms, which is where choices about technology are made, rather than in industries or regions.

5.2 Estimation methodology

Estimation of equation (5) by least squares is unlikely to be consistent for three reasons: (a) endogeneity of the included right hand side variables; (b) correlation of the included right hand side variables with relevant omitted variables; and (c) sample selection. Here we describe our instrumental variables strategy that delivers a consistent estimator of (5) in the face of these three issues, and we discuss potential threats to the internal validity of our IV approach.

Our data cover the 14 years 1994 to 2007. As noted above, there are some small discontinuities in the hours shares between 2001 and 2002 due to data reclassification. Consequently, we estimate equation (5) on the 5 year period 2002 to 2007. That is, the left hand side variable Δs_{fot} is the change in ex-techie hours share between 2002 and 2007, and the initial levels of techies and trade on the right hand side are measured in 2002. Because our data goes back to 1994, we use lagged levels of techies and trade from 1994 to 1998 as instruments for the levels of techies and trade in 2002 (our choice of which years to use as instruments is discussed below). We estimate (5) for each of the 12 large PCS occupations, separately for manufacturing and nonmanufacturing firms, which amounts to 24 separate regressions.

Our estimation sample consists of a balanced panel of the 310,713 French private sector firms that have positive hours worked in each year from 1994 to 2007. We refer to these as "permanent firms". Thus, firm entry and exit is not relevant to our estimation strategy, though many firms do add and drop occupations over time (we discuss the implications of this for estimation below). These 310,713 firms, 85% of whose hours worked are in nonmanufacturing, account for about half of private sector hours worked in each year, and they are somewhat larger than the average firm, both in terms of total hours and in the average number of occupations per firm. Figure 8 illustrates the differences between the French private sector as a whole and our estimation sample of permanent firms. For most occupations, the differences are small and stable over time, and the exceptions are small occupations. Figure 9 shows that overall changes in hours shares and the within-between split are similar for permanent firms and those that are active for a subset of the sample ("temporary firms").

5.2.1 Instrument validity

As with any IV strategy, consistency requires that the lagged independent variables satisfy three requirements: they must be strong (correlated with the included endogenous variables), excludable (not relevant for determining Δs_{fot}), and exogenous (uncorrelated with the composite error term u^o_{it}). We address these requirements in turn, but in summary: our instruments are undoubtedly excludable and strong, but there are some concerns about exogeneity.

Are the instruments excludable? Under the maintained hypothesis that our instruments are exogenous, we implement an intuitive and straightforward test of the excludability of our instruments from (5). Our procedure is to add the 1998 lag of techies and trade to (5), using lags from 1994 to 1997 as instruments. We then test the null hypothesis that the coefficients on the 1998 levels are jointly zero. The question being asked by this procedure is: once we have controlled for 2002 levels of techies and trade, is there any extra explanatory power from the 1998 levels? This null can not be rejected in most cases, which leads us to proceed in assuming that the exclusion restrictions for lags from 1994 to 1998 are valid.

Are the instruments strong? In applied work, the most common test statistic of the null of weak instruments is the first stage F-statistic, where the critical values are somewhat larger than the standard tabulation of the F distribution would indicate (Staiger and Stock (1997)). As discussed by Stock and Yogo (2005), the econometric theory of testing for weak instruments when there is more than one endogenous regressor is challenging, and results only exist for the case of up to three endogenous regressors (see Table 1 in Stock and Yogo (2005)). Since our application includes six endogenous regressors, there is no econometric theory available to guide the choice of critical values for a first stage F statistic. As an alternative, we report Shea (1997)'s partial R^2. Shea's statistic, along with other measures of first stage goodness-of-fit, has been criticized because it lacks a foundation in distribution theory, but it has two key virtues: it is easy to interpret, and it is well defined for an arbitrary number of endogenous variables.

The instrument strength diagnostics for equation (5) are reported in Table 5. The message from this table is simple: for all six endogenous variables, all twelve PCS codes, and both non-manufacturing and manufacturing sectors, the first-stage Shea's partial R^2 leaves no doubt that our instruments are strong. This is not surprising, since our instruments are lagged values of the endogenous regressors. This conclusion also holds for equation (9), which we discuss below, as shown in Table 12.

Are the instruments exogenous? For the instruments to be exogenous, they must be uncorrelated with the composite error term u_{it}^o in (5). Recall that u_{it}^o includes both changes in firm characteristics x_{kft} and changes in the error term ε_{fot} in (4). Thus our identifying assumption is that five year *changes* in the x_{kft}'s and the error term ε_{fot} are uncorrelated with four to eight year lags of the *levels* of techies and trade.

We can directly test part of our exogeneity assumptions, because 2002–2007 changes in techies and trade are among the changes in firm characteristics included in u_{it}^o, and we have data on these changes. As a test of the null hypothesis that these observable changes are uncorrelated with the instruments, we regress 2002–2007 changes in techies and trade on the full set of instruments. The explanatory power of these regressions is near zero: the R^2's regressions are tiny, and F tests fail to reject the null of no linear relationship.

While reassuring, these regression tests of instrument exogeneity fail to address potential correlation between the instruments and changes in *unobservable* firm characteristics such as revenue or capital and intermediates intensity. However, given the very low correlation between changes and lagged levels in the variables we *do* observe, it seems reasonable to expect that the correlation between changes in different variables and our instruments would also be small.

An additional concern is endogeneity in the instruments due to serial correlation in the error term ε_{fot} in (4). It is likely that the errors are contemporaneously correlated with the x_{kft}'s, so serial correlation in ε_{fot} implies possible correlation between ε_{fot} and the lagged x_{kft}'s that we use as instruments. However, since it is $\Delta\varepsilon_{fot}$ rather than ε_{fot} that enters our estimating equation (5), what matters for the exogeneity of our instruments is possible correlation between $\Delta\varepsilon_{fot}$ and the lagged x_{kft}'s. In the appendix we show that although serial correlation in ε_{fot} does give rise to bias, this bias is likely to be small.

As we have just argued, the above issues are likely to be minor threats to the exogeneity of our instruments. A more serious concern is omitted variables in initial period levels in equation (5). Potentially important omitted variables include other firm inputs such as capital, materials, and domestic outsourcing. If the omitted variables in levels are both contemporaneously correlated with our regressors and correlated over time, then they may be correlated with our instruments. We regard this possibility as the most serious threat to the exogeneity of our instruments, and it is not one that we can test for or rule out *a priori*.

Table 15 reports p-values for two standard diagnostic tests for 2SLS estimation of equation (5). The rows labeled "Endogeneity, $\chi^2(6)$" test the null hypothesis that OLS is a consistent estimator using a Hausman test, while the rows labeled "Overid, $\chi^2(24)$" test the null hypothesis that the instruments are valid using Hansen's J test.[30] As is common in applied work, in most cases we reject both nulls at conventional significance levels. Taken literally, the implication is that OLS is inconsistent, but that our instruments are not exogenous. The purpose of the discussion above is to argue that while our instruments are imperfect, 2SLS is likely to have smaller bias than OLS, so we proceed accordingly.

Choice of instruments Since our estimation period begins in 2002, while the sample begins in 1994, we potentially have eight lags, 1994 to 2001, of the dependent variables to use as instruments. This raises two distinct questions. The first is, how many lags are exogenous? The second question is, if all the lags are exogenous, how many should be used as instruments? This second question is motivated by the fact that even if all eight lags are valid instruments, there is the potential for finite sample bias due to the "many instruments" problem (see Bound, Jaeger, and Baker (1995) for an illustration).

To answer the question about how many instruments are valid, we implement a sequence of "difference-in-Sargan" tests. We assume that the 1994 lag is a valid instrument, and we then sequentially add more recent lags (1995, 1996, etc.). The incremental increase in the usual overidentification test statistic is distributed as a χ_1^2, and failure to reject the null is taken as evidence for instrument validity. The results indicate that no more than five lags, including 1994, should be used. That is, conditional on the exogeneity of the 1994–1998 lags, we reject the null hypothesis that 1999 and subsequent lags of $\mathbf{X}$ are exogenous[31].

To answer the question about how many valid instruments to use, we use the procedure proposed by Donald and Newey (2001). The purpose of the Donald-Newey procedure is to select the most efficient set of instruments, and the procedure involves minimizing the mean squared error (MSE) of a weighted average of the estimates of interest, relative to a benchmark estimate.[32] Our benchmark uses only the 1994 lags of $\mathbf{X}$. We consider the simple average of the MSE criterion across the six elements of $\boldsymbol{\beta}$. When we add lags of $\mathbf{X}$ sequentially and compare the MSE to that of using only 1994, we find that the minimum MSE is attained with six or seven lags, which includes 1999 or 2000, respectively.

[30] There are six degrees of freedom for the Hausman test because there are six endogenous variables in (4). With five lags of the six dependent variables, we have 30 instruments, which is why there are 24 degrees of freedom for the J test.

[31] The results vary somewhat across occupations, but on average, five lags, from 1994 to 1998 are the maximum.

[32] Of the two minimum MSE crieria proposed by Donald and Newey (2001), we use the Mallows criteria, which proves to be more robust.

To summarize, our two procedures give slightly different answers, with the difference-in-Sargan procedure suggesting using 1994-1998 lags and the Donald-Newey procedure suggesting an additional year or two. We choose to be conservative, and thus proceed by using the 1994–1998 lags as our set of instruments.

5.2.2 Censoring

Firms choose their mix of occupations optimally, and corner solutions are common: few if any firms employ workers in all occupations in every year, and the median number of occupations per firm-year is 10.[33] This means that the sample size when estimating (5) varies by PCS code.[34] If corner solutions in occupational hours are nonrandom and correlated with observables, which is likely, then OLS is inconsistent. Rather than trying to model sample selection, which is neither feasible nor relevant to our research question, we rely on our instruments to correct for the inconsistency due to sample selection.

5.2.3 Weighting

The unit of observation in our data is a firm, but our research question concerns employment. Since the distribution of employment across firms is highly skewed, unweighted regression analysis of (5) would weight tiny firms the same as huge firms, which would give a distorted picture of the effect of techies and trade on employment polarization. To avoid this, our estimator weights firm observations by total firm hours in 2002. The resulting estimates have the usual interpretation as estimated conditional means, where the conditional expectation is taken over the distribution of hours worked rather than the distribution of firms. Our practice of weighting by employment is standard in the literature on inequality and polarization, see for example Michaels, Natraj, and Van Reenen (2014) and Autor and Dorn (2013).

5.2.4 Summary of estimation strategy

To summarize our estimation strategy for equations (5) and (6),

- 24 regressions (12 PCS occupations, manufacturing and nonmanufacturing firms)
- Dependent variable is change in ex-techie occupation share of hours worked, 2002-2007.

[33] More precisely, 10 is the weighted median, with weights equal to total firm hours in the permanent-private subsample of firms used in our regression analysis. The weighted median is 12 for manufacturing firms, and 9 for nonmanufacturing firms.

[34] When $s_{fot} = s_{fot-1} = 0$, we treat the change Δs_{fot} as undefined, and firm f is not included in the estimation sample for occupation o.

- Explanatory variables are levels of techies (share of hours) and trade (imports and exports, scaled by total firm wage bill) in 2002.
- Estimator is weighted two stage least squares.
- Instruments are lagged techies and trade, 1994-1998.
- Observations weighted by firm hours worked in 2002.
- Heteroskedasticity robust covariance matrix.

5.3 Estimation results

The estimated parameters of equations (5) and (6) do not directly address our research questions, so we relegate parameter estimates to the Appendix. Here we focus on two questions:

1. What is the effect of an increase from zero to the median of the explanatory variable on the change in the ex-techie share? We call this the *extensive margin effect.*
2. What is the effect of an increase from the 25^{th} to the 75^{th} percentile of the explanatory variable on the change in the ex-techie share? We call this the *intensive margin effect.*

We scale both estimated effects by the 75^{th}-25^{th} percentile range (also called the interquartile range or IQR) of the change in the ex-techie share.[35] Computing these effects involves calculating the estimated conditional mean at two different points, and then looking at the difference. For equation (5), the formulas for the extensive and intensive margin effects of techies on occupation o are, respectively,

$$extensive\_techies_o = \frac{\widehat{\beta}_2^o + \widehat{\beta}_1^o \times p50\,(techies^o)}{p75\,(\Delta s_o) - p25\,(\Delta s_o)} \tag{7}$$

$$intensive\_techies_o = \frac{\widehat{\beta}_1^o \times [p75\,(techies^o) - p25\,(techies^o)]}{p75\,(\Delta s_o) - p25\,(\Delta s_o)} \tag{8}$$

where $pN(x)$ is the N^{th} percentile of variable x. Analogous definitions apply to the intensive and extensive margin effects of imports and exports. The effects defined by (7) and (8) are unit-free, and their scale is comparable across occupations. To understand the scale, suppose that the estimated extensive margin effect of techies is 0.6. This means that an increase from zero to the median value of techies increases the expected change in the ex-techie employment share, Δs_{fot}, by 60% of its

[35] For the explanatory variables, in computing the intensive and extensive margin effects we use the percentiles of the distribution of strictly positive values.

interquartile range (IQR). Similarly, an intensive margin effect of techies of -0.4 means that a one IQR change in techies causes an expected reduction of Δs_{fot} equal to 40% of its IQR. In short, the effects we report are quite similar to elasticities.

The interaction effects estimated in equation (6) permit us to refine the above questions. In particular, we can ask: what are the intensive and extensive margin effects of techies for firms that trade and those who do not trade? Similarly, we can ask: what are the intensive and extensive margin effects of imports and exports for firms with and without techies? As with the simpler formulas given by (7) and (8), the formulas for the differences in conditional means involve both parameter estimates and percentiles of the data. The somewhat involved expressions for these effects are relegated to the Appendix, as are the parameter estimates for equations (5) and (6). Tables 6 and 7 report the size of relevant subsamples.[36]

Tables 8 through 11 report our results. Rows are occupation-specific regression results. The *Overall* effects in columns (1) and (2) of Tables 8 through 11 are functions of the data and the estimated parameters of our baseline specification, equation (5). The remaining columns are functions of the data and the estimated parameters of (6). Statistically significantly effects are shaded, and standard errors are reported in italics.[37]

5.3.1 Techies cause within-firm skill upgrading in nonmanufacturing

Turning first to the estimates for nonmanufacturing firms (over 85% of private sector employment), the *Overall* results in Table 8 show that techies have a large positive effect on within-firm skill upgrading:

- Firms with more techies have statistically significantly higher employment growth of top managers (PCS 37), and the effect is large. The extensive margin effect, which compares a firm with no techies to one with a median techie share, is that the latter has growth in the managerial share of hours that is higher by 34% of the interquartile range (IQR). Turning to the intensive margin effect among firms with techies, the effect of a one IQR higher techie share is to raise growth of the managerial share by a fifth of its IQR.
- Among other white collar workers, the intensive margin effect of techies is to cause modest skill upgrading: middle-management jobs grow faster (PCS 46, effect is +0.048) while low-

[36] Because firms that only import or only export comprise such a small share of hours worked (16 percent of hours in nonmanufacturing, 9 percent in manufacturing) and of trade (10 percent of trade in nonmanufacturing, 1 percent in manufacturing), we do not report the estimated effects for these firms. Complete results are reported in the Appendix.

[37] That is, estimates with 90% confidence intervals that exclude zero are shaded.

paid office and retail occupations grow more slowly (the effect for Office Workers PCS 54 is -0.055, and for Retail Workers PCS 55 it is -0.15).

- The lowest-paid occupation, low-skill manual workers (PCS 68), grew much more slowly in firms with techies, with an extensive margin effect of -0.67. The intensive margin effect of -0.20, while smaller, is also economically important.
- By contrast, the extensive margin effect of 1.46 for highly paid skilled industrial workers (PCS 62) is large and positive: firms with the median number of techies saw their share of PCS 62 increase much faster than firms with no techies.[38]
- The final 4 columns of Table 8 shows how the effect of techie varies with firm's trading status:
  - For firms that do not trade (58 percent of hours worked in nonmanufacturing), the extensive margin effect of techies on top manager growth (PCS 37, +0.5) is half again as big as the effect for firms overall. There are no statistically significant effects for other white collar occupations (PCs 46 to 56), but there is a strong skill upgrading effect within blue collar workers, particularly along the extensive margin: techies cause faster growth for skilled industrial (PCS 62, +1.4) and transport/logistics workers (PCS 65, +0.7), and slower growth for low-skill manual laborers (PCS 68, -0.7).
  - For firms that both import and export (26 percent of hours worked), the extensive margin effects of techies in column 5 are unidentified, which is a consequence of the fact that over 90 percent of hours worked among this group of firms are in firms with techies (see Table 6). The intensive margin effects in column 6 generally line up with the overall intensive margin effects reported in column 2.

5.3.2 Techies cause within-firm skill polarization in manufacturing

Table 9 shows that rather than causing skill *upgrading* as they do in nonmanufacturing, techies in manufacturing cause skill *polarization.* The channels are mainly along the extensive margin, and are somewhat different among firms that trade and those that do not:

- Among firms that trade (78 percent of hours worked in manufacturing), polarization occurs within white collar workers, with middle managers growing faster (PCS 46, +0.6) and clerical workers growing sharply slower (PCS 54, -0.9), both along the extensive margin (the intensive margin effects have the same sign but are smaller).

[38] Despite our short-hand description of PCS 62 as "skilled industrial workers", this occupation comprised more than 4 percent of hours worked in nonmanufacturing in 2002 (see Table 3), mainly in construction.

- Within non-trading firms (14 percent), the extensive margin polarization effect of techies was even sharper. In firms with techies, top and middle managers grew faster (PCS 37, +0.8 and PCS 46, +0.5) while within blue collar workers techies caused *skill downgrading*, with skilled industrial workers growing much more slowly (PCS 62, -1.3) and low-skill blue collar workers growing faster (PCS 67, +1.5). The effect for clerical workers is also negative (PCS 54, -0.5) though not statistically significant.

5.3.3 Trade affects within-firm skill mix in manufacturing

Tables 10 and 11 show that trade also affects the within-firm occupational mix, but mainly in manufacturing. Looking first at nonmanufacturing firms,

- The more that firms trade, the faster their growth in top managers (PCS 37), but the effect is small, +0.02 for both imports and exports (columns 2 and 6 of Table 10).
- Compared to firms that do not export, firms that export and also have techies (column 7 of the table) have sharply falling shares of supervisors (PCS 48, -0.8) and office workers (PCS 54, -0.8) and rising shares of retail workers (PCS 55, +0.7) and low skill manual workers (PCS 68, +3.4).
- Overall, importing has small and mainly statistically insignificant effects on the occupational mix.

Given that nonmanufacturing firms do not engage in much direct international trade, the lack of strong results just described is not surprising. In Table 11 we find much larger effects of trade on manufacturing firms, almost entirely along the extensive margin.

- The extensive margin of exporting has a large and positive effect on growth in the share of managers, PCS 37. The overall effect of +0.4 (column 5) is similar in size, though imprecisely estimated, among firms with techies. By contrast, importing has no extensive margin effect on the PCS 37 share.
- there is a strong blue collar skill *upgrading* effect of importing (column 1): the growth of skilled industrial and manual laborers (PCS 62 and 63) is much faster (+1.3 for PCS 62 and +6.2 for PCS 63), while growth of unskilled industrial workers is much slower (PCS 67, -3.3).
- there is a strong blue collar skill *downgrading* effect of exporting (column 5): the growth of skilled industrial and manual laborers (PCS 62 and 63) is much slower (-1.0 for PCS 62 and

-3.4 for PCS 63) while the share of unskilled industrial workers grows much faster (PCS 67, +2.1).

The intensive margin effects of trade in manufacturing industries are mostly small and/or statistically insignificant—all the action comes from comparing firms that do not trade with firms that do. The effects for firms with techies (columns 3, 4, 7, and 8) are very similar to the overall effects, which is to be expected since virtually all manufacturing firms that trade also have techies (last line of Table 7).

For manufacturing firms, imports are primarily of intermediate inputs, so we have identified the effects of offshoring. The skill upgrading effect of importing is consistent with a simple offshoring story where imported intermediate goods substitute for low-skill workers within manufacturing firms, thus raising the skill intensity of the remaining labor force. This is consistent with Biscourp and Kramarz (2007), who find that imports of final goods are associated with declines in production workers' employment, and in particular low-skill production workers' employment in French Manufacturing in 1986–1992. It is also what is found by Verhoogen (2008) in Mexican data.[39]

Our finding that exporting is associated with faster growth of managers (PCS 37) is not surprising, given the extensive literature that documents a positive correlation between the share of non-production/white-collar jobs and exporting. What is new and puzzling is our finding that exporting causes skill *downgrading* within production/blue-collar occupations. Together these results imply a within-firm polarizing effect of exporting. Earlier researchers using plant or firm level data could not uncover this effect because they did not have information on skill composition within production/blue-collar workers.

6 Econometric analysis of between-firm differences in employment growth

In this section we turn to a different research question: what accounts for differences across firms in employment growth? As in section 5, our hypothesis is that both globalization and technological change are important causal factors, and the purpose of our econometric analysis is to quantify their importance.

[39] Verhoogen (2008), studies the effects on plant-level quality upgrading in manufacturing in Mexico, following the large 1994/1995 devaluation of the peso. He proxies worker quality by within-blue collar education levels in manufacturing.

6.1 Estimating equations and estimation methodology

Our estimation approach here is very similar to the approach in section 5, so we move quickly. In Section 4 we saw that a drop in computer prices will increase the competitiveness, and potentially employment, of more ICT-intensive firms relative to less ICT-intensive firms. Globalization may also affect firm-level employment. We test these hypotheses by estimating regressions similar to those estimated in section 5, where we replace the dependent variable Δs_{fot} with total employment growth of the firm g_{ft} between 2002 and 2007. To control for the well-known fact that larger firms grow more slowly, we also include log initial firm employment as a control. Thus, our estimating equation is

$$g_{ft} = \beta_i + \boldsymbol{\beta}\mathbf{X}_{ft-1} + u_{ft} \ , \tag{9}$$

where $\mathbf{X}$ includes the regressors in equations (5) and (6), plus log total hours in 2002[40]. The estimator is again weighted two-stage least squares, where the weights are 2002 hours worked. The issues of instrument strength and validity are the same as before, and Table 16 reports p-values for the Hausman endogeneity test and Hansen's J test of the overidentifying restrictions. Table 12 shows that the first stage is strong. The estimation sample is the set of "permanent" firms that were active from 1994 onwards. As a result sample selection is not an econometric concern.

Firm-level imports are likely to have different effects on employment growth depending on what goods are imported. For example, imports of capital goods or final goods that are complementary in demand to the goods produced by a firm (Bernard, Blanchard, Van Beveren, and Vandenbussche (2012)) may boost employment, while offshoring (imports of parts and other intermediates) may reduce employment growth. To allow for these differences, we report estimates that break down imports by intermediate/final and by source country.

6.2 Estimation results

Rather than report regression estimates, we report estimated extensive and intensive margins effects of trade and techies on employment growth, using the same expressions described in (7) and (8), separately for nonmanufacturing and manufacturing firms.

6.2.1 Techies cause faster employment growth, especially in manufacturing

The effect of techies are reported in Panel A of Table 13, first for all firms (columns 1 and 2) and then for firms divided into those who do and do not trade (columns 3 through 6).

[40] log hours in 2002 are treated as endogenous, and we use log hours from 1994 to 1998 as additional instruments.

- The first number in Table 13, 0.344, means that nonmanufacturing firms with the median techie share saw significantly faster employment growth than firms without techies. At one third of the interquartile range (IQR) of employment growth, this is an economically large effect.

- The extensive techie effect for nonmanufacturing firms is the same for firms that do not trade (column 3, almost 60% of employment within nonmanufacturing), and there is also a small 0.15 intensive margin effect for these firms (column 4). For firms that trade (column 5) the extensive margin effect is not significant, and there is a small negative intensive margin effect (column 6).

- Techies have a strong effect on manufacturing employment growth, with an extensive margin effect of 0.94 and a smaller but still important intensive margin effect of 0.22 (columns 1 and 2). The extensive margin effect is particularly strong for firms that do not trade (column 3), and is positive but not significant for firms that do trade (column 5). The fact that the extensive margin effect of techies is imprecisely estimated for firms that trade is due to the fact that almost all trading firms employ techies (Table 6).

Overall, Panel A of Table 13 shows that firms that employed techies in 2002 saw much faster employment growth from 2002 to 2007. The same is true for non-trading manufacturing firms. This result is consistent with our theoretical prediction in Section 4, where we illustrated that falling ICT prices raise the competitiveness of firms that employ techies.

6.2.2 Trade affects employment growth

The effects of importing and exporting on employment growth are reported in Panel B of Table 13, first for all firms (columns 1, 2, 5 and 6) and then for firms divided into those who do and do not employ techies (columns 3, 4, 7, and 8). All but one of the estimated effecst are statistiaclly insignificant, and the one significant effect is trivially small.

The empirical literature on offshoring suggests (e.g., Biscourp and Kramarz (2007)) that it is important to distinguish between intermediate inputs and other imports, and among country sources of imports. To do this we estimate versions of equation (9) that disaggregate trade, first by including an indicator for imports of intermediate goods and second by disaggregating imports by source country (high income countries according to World Bank classification in 2002, China, and all other countries). These import measures enter the regression as in all our other specifications, as intensity (value divided by total gross wage bill) and as an indicator for positive values.

The results from these specifications are reported in Table 14. The first two columns repeat the "overall" estimates from Table 13. Columns 3 and 4 report estimates when we add regressors that capture intermediate inputs. In this specification the effect of importing intermediate inputs is incremental, over and above importing *per se*. Columns 5 and 6 disaggregate by sources of imports. Our findings are:

- Column 3 shows that for manufacturing firms, importing *per se* has a statistically insignificant positive extensive margin effect, but the extensive margin of imports of intermediates is large and negative, at -0.8. The negative employment growth effects of importing intermediate inputs (that is, offshoring) is suggestive of a simple substitution effect of foreign for domestic labor, which is also what we found in Table 11. We thus find no evidence of a firm-level productivity effect of offshoring that offsets the labor substitution effect, as seen in the models of Grossman and Rossi-Hansberg (2008) and Rodriguez-Clare (2010).

- When distinguishing imports by source country (columns 5 and 6), we still find that the effects are insignificant for nonmanufacturing firms. But the story for manufacturing firms is strikingly different: the overall insignificant effect found in column 1 is evidently hiding large negative effects from lower income countries (-0.1 but insignificant from China and -0.43 from other), combined with a zero effect for imports from rich countries. This is consistent with the idea that offshoring to lower income countries reduces employment growth by substituting imported intermediate inputs for labor

- Exporting has no detectable effect on employment growth in any specification (the extensive margin effects are small and positive and the intensive margin effects are small and negative, but none are precisely estimated).

Overall, our results in Tables 11 and 14 support a conclusion that offshoring reduces firm employment growth, and leads to skill upgrading within blue collar workers.

7 Econometric Results: Goodness of fit

We now turn to a different question: how much of the within-firm and between-firm variation in occupational change do our econometric models explain? To answer this, we compute two measures. The first is the usual regression R^2, weighted by firm hours. The second is directly related to the within-between decomposition of occupational hours share changes given by equation (1). We first compute the "explained within" component from 2002 to 2007 using the fitted values $\widehat{\Delta s}_{fot}$ from estimation of equation (5), and then divide this by the actual within component for permanent firms from 2002 to 2007,

$$\textit{Explained within}_o = 100 \times \frac{\sum_f \overline{\lambda}_f \widehat{\Delta s}_{fot}}{\sum_f \overline{\lambda}_f \Delta s_{fot}} \ ,$$

where $\overline{\lambda}_f$ is the average hours share of firm f from 2002 to 2007.[41] *Explained within* is an answer to the question, "what percentage of the within-firm change in the hours share of occupation o from 2002 to 2007 is explained by the estimates?". Similarly, we compute the "explained between" component from 2002 to 2007 using the fitted values $\widehat{g}_{ft}$ from estimation of equation (9), and then divide this by the actual between component for permanent firms from 2002 to 2007,

$$\textit{Explained between}_o = 100 \times \frac{\sum_f \widehat{\Delta\lambda}_{ft} \overline{s}_{fo}}{\sum_f \Delta\lambda_{ft} \overline{s}_{fo}} \ ,$$

where $\widehat{\Delta\lambda}_{ft}$ is approximated by using $\widehat{g}_{ft}$.[42]

Table 15 reports the weighted R^2 and *Explained within* goodness of fit statistics for the estimates of our baseline specification, equation (5). Similarly, Table 16 reports the weighted R^2 and *Explained between* goodness of fit statistics for the estimates of equation (9). The R^2s are generally very low, which is to be expected in cross sectional micro data.

The *Explained within* results are generally weak, with 9 of the 24 being negative, which means that the regression model predicts an aggregate change opposite in sign to what actually occurred. Of the 15 positive results, only 5 are greater than 1 percent. The *Explained between* results in Table 16 are even weaker, with 11 of the 24 being negative - barely better than a coin flip. The inability of the regression model to explain much of the within-firm and between-firm variation is probably a sign of the importance of both firm-specific random shocks and unmeasured systematic influences on firms' occupational choices.

Tables 15 and 16 also report p-values for the null hypothesis that the trade and techie effects are jointly equal to zero. This null is rejected for equation (5) at conventional significance levels for all the PCS codes in manufacturing, and for nine of twelve in non-manufacturing. For equation (9) this null is rejected for both nonmanufacturing and manufacturing.

[41] Since the regression model explains the ex-techie share of occupation o in firm f, which is weakly greater than the overall share of o in f, we adjust the fitted values by multiplying them by the average ratio of ex-techie to total hours for f in the two years.

[42] We explain how we approximate $\widehat{\Delta\lambda}_{ft}$ by using $\widehat{g}_{ft}$ in the appendix.

8 Conclusions

In this paper we use administrative employee-firm-level data from 1994 to 2007 to show that the labor market in France has become polarized: employment shares of high and low wage occupations have grown, while middle wage occupations have shrunk. During the same period, the share of hours worked in technology-related occupations ("techies") grew substantially, as did imports and exports, and we explore the causal links between these trends.

We show that polarization is pervasive: it has occurred within the nonmanufacturing and manufacturing sectors, and both within and between firms. The importance of between-firm reallocations for polarization implies that simple theories of substitution across workers miss an important margin of adjustment.

Motivated by the fact that technology adoption is mediated by technically qualified managers and technicians, we develop a novel measure of the propensity to adopt new technology: the firm-level employment share of techies. Using the subsample of firms that are active over the whole period, we develop an empirical framework that allows us to study the firm-level effects of falling ICT prices and the growth of offshoring and exporting. To control for the endogeneity of firm-level techies and trade in 2002, we use values of techies and trade from 1994 to 1998 as instruments.

Our econometric results show that nonmanufacturing firms with more techies in 2002 saw substantial skill *upgrading* from 2002 to 2007, with the share of hours worked by managers growing faster and the share worked by office and retail workers growing slower. The effect of techies in manufacturing was polarizing, but differed between firms that traded and those that did not: firms that did not trade saw their share of managers rising faster and blue-collar skill *downgrading,* while firms that traded saw faster growth in middle managers as office workers grew more slowly.

Our results also show that firms with more techies in 2002 saw substantially faster employment growth in 2002–2007. This is consistent with technological change improving the competitiveness of these firms relative to other firms with no techies in 2002.

Importing by manufacturing firms caused blue-collar skill *upgrading*, suggesting that low-skill blue collar workers saw their tasks replaced by imports. Exporting is found to cause within-firm *polarization*: faster growth in the share of managers and skill *downgrading* within production workers. Offshoring also causes slower employment growth in manufacturing, while exporting has no effect on employment growth.

While our estimated effects of techies and trade are economically large, most of the variation in within-firm and between-firm occupational change is unexplained by these variables. We thus make no claim that the mechanisms we study in our econometric exercises are the only, or even dominant, influences on changes in the aggregate occupational mix.

Changes in the occupational structure of employment are an important feature of the world economy in recent decades, with profound implications for inequality and for the distribution of gains from technological progress and globalization. Our paper is the first to analyze these economy-wide changes using firm-level data, which has made it possible to paint a rich and nuanced portrait of how and why polarization evolved in France between 1994 and 2007.

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9 Figures and Tables

Table 1: PCS Occupations

PCS code	description of occupation	rank	share
21	Small business owners and workers	7	0.1
22	Shopkeepers	3	0.2
23	Heads of businesses	1	0.7
34	Scientific and educational professionals	5	0.5
35	Creative professionals	6	0.6
37	**Top managers and professionals**	**2**	**7.3**
38	**Technical managers and engineers**	**4**	**6.2**
42	Teachers	9	0.3
43	Mid-level health professionals	12	1.2
46	**Mid-level managers & professionals**	**11**	**12.2**
47	**Technicians**	**10**	**5.0**
48	**Supervisors and foremen**	**8**	**2.9**
53	Security workers	18	1.0
54	**Office workers**	**16**	**11.6**
55	**Retail workers**	**20**	**7.0**
56	**Personal service workers**	**21**	**4.1**
62	**Skilled industrial workers**	**13**	**11.0**
63	**Skilled manual laborers**	**17**	**8.5**
64	**Drivers**	**14**	**5.1**
65	**Skilled transport and wholesale workers**	**15**	**2.7**
67	**Unskilled industrial workers**	**19**	**8.2**
68	**Unskilled manual laborers**	**22**	**3.7**

Note to Table 1: "rank" is the occupation's wage rank in 2002, "share" is occupation's share of hours worked in 2002. Occupations in bold are account for at least 2.5 percent of hours worked.

Table 2: PCS 2-digit occupations and representative 4-digit suboccupations

37	**Top managers and professionals**	**56**	**Personal service workers**
	Managers of large businesses		Restaurant servers, food prep workers
	Finance, accounting, sales, and advertising managers		Hotel employees: front desk, cleaning, other
	Other administrative managers		Barbers, hair stylists, and beauty shop employees
38	**Technical managers and engineers (techies)**		Child care providers, home health aids
	Technical managers for large companies		Residential building janitors, caretakers
	Engineers and R&D managers	**62**	**Skilled industrial workers**
	Eletrical, mechanical, materials and chemical engineers		Skilled construction workers
	Purchasing, planning, quality control, and production managers		Skilled metalworkers, pipefitters, welders
	Information technology R&D engineers and managers		Skilled heavy and electrical machinery operators
	Information technology support engineers and managers		Skilled operators of electrical and electronic equipment
	Telecommunications engineers and specialists		Skilled workers in various industries
46	**Mid-level professionals**	**63**	**Skilled manual laborers**
	Mid-level professionals, various industries		Gardeners
	Supervisors in financial, legal, and other services		Master electricians, bricklayers, carpenters, etc
	Store, hotel, and food service managers		Skilled electrical and electronice service technicians
	Sales and PR representatives		Skilled autobody and autorepair workers
47	**Technicians (techies)**		Master cooks, bakers, butchers
	Designers of electrical, electronic, and mechanical equipment		Skilled artisans (jewelers, potters, etc)
	R&D technicians, general and IT	**64**	**Drivers**
	Installation and maintenance of non-IT equipment		Truck, taxi, and delivery drivers
	Installation and maintenance of IT equipment	**65**	**Skilled transport workers**
	Telecommunications and computer network technicians		Heavy crane and vehicle operators
	Computer operation, installation and maintenance technicians		Warehouse truck and forklift drivers
48	**Foremen, Supervisors**		Other skilled warehouse workers
	Foremen: construction and other	**67**	**Low skill industrial workers**
	Supervisors: various manufacturing sectors		Low skill construction workers
	Supervisors: maintenance and installation of machinery		low skill electrical, metalworking, and mechanical workers
	Warehouse and shipping managers		low skill shipping, moving, and warehouse workers
	Food service supervisors		Other low skill transport industry workers
54	**Office workers**		Low skill production workers in various industries
	Receptionists, secretaries	**68**	**Low skill manual laborers**
	Administrative/clerical workers, various sectors		Low skill mechanics, locksmiths, etc
	Computer operators		Apprentice bakers, butchers
	Bus/train conductors, etc		Building cleaners, street cleaners, sanitation workers
55	**Retail workers**		Various low skill manual laborers
	Retail employees, various establishments		
	Cashiers		
	Service station attendants		

Figure 2: Occupational Hours Shares

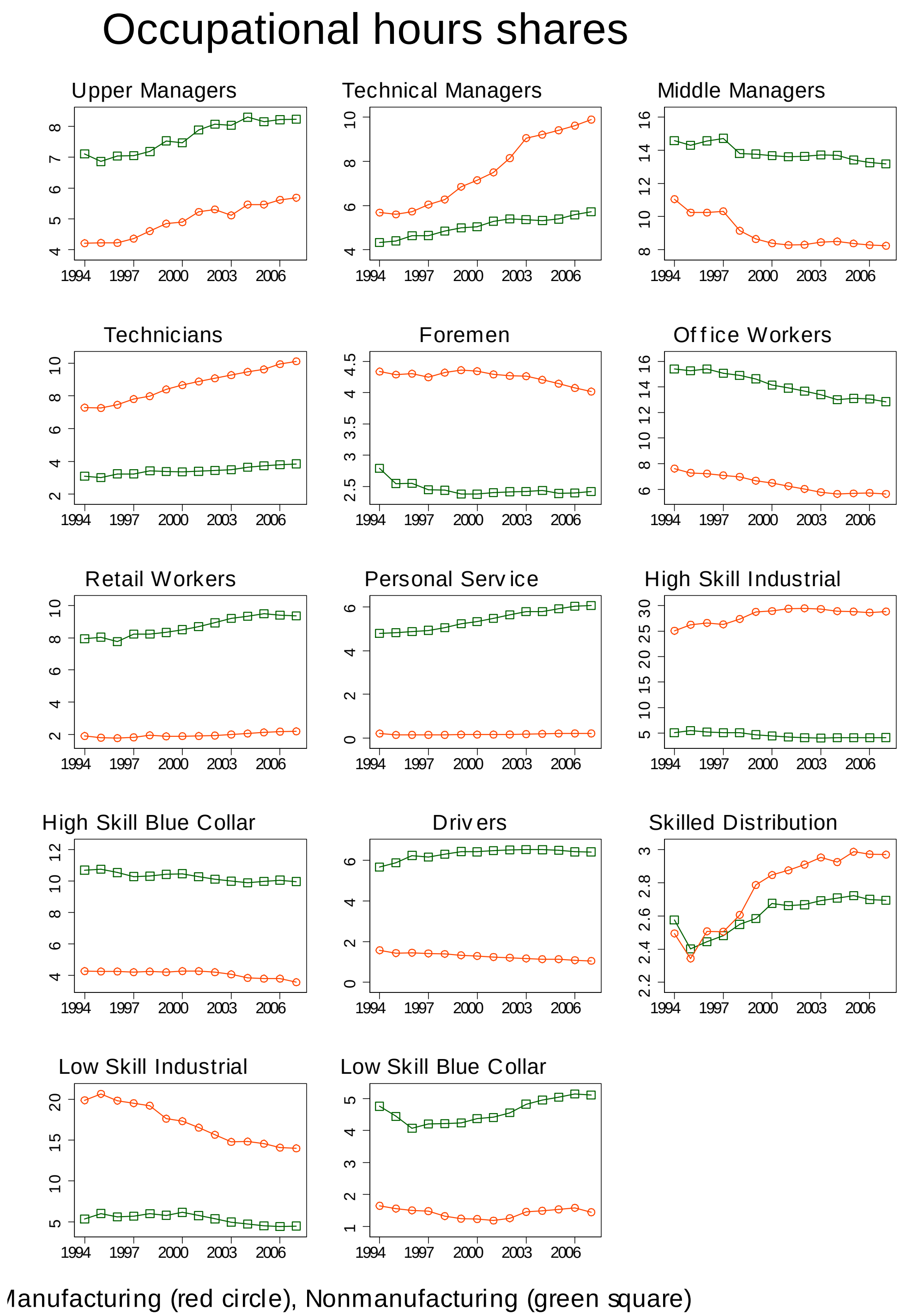
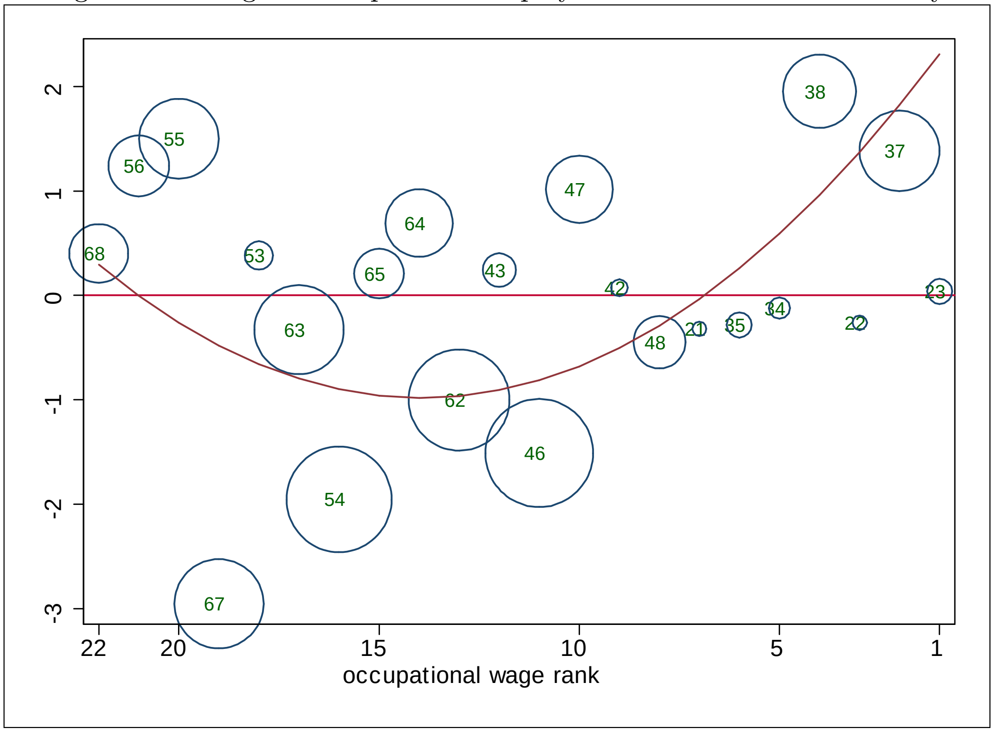


Figure 3: Change in occupational employment shares - whole economy



Notes to Figures 3, 4, and 5: Vertical axis is change in occupation's share of aggregate hours worked from 1994 to 2007. Horizontal axis is rank of occupation's average wage in 2002. Circles are labelled by PCS occupation and are proportional in size to occupation's share of hours worked in 2002. Curve is fitted values from a weighted regression of hours share change on rank and rank^2. For key to occupations, see Tables 1 and 2.

Figure 4: Change in occupational employment shares - Nonmanufacturing

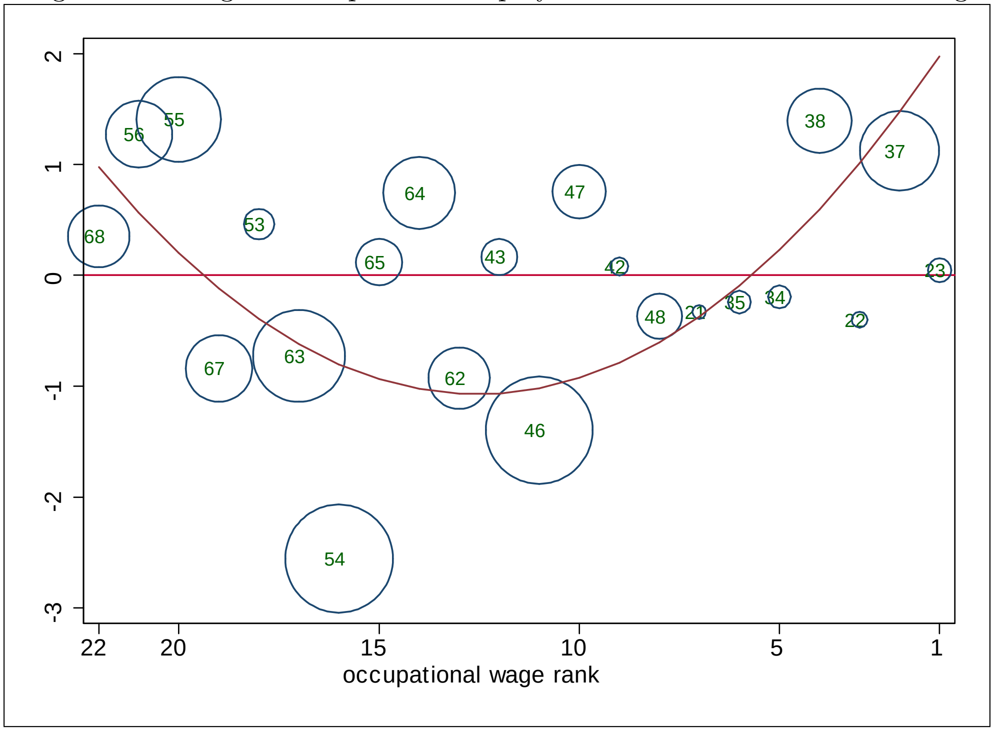


Figure 5: Change in occupational employment shares - Manufacturing

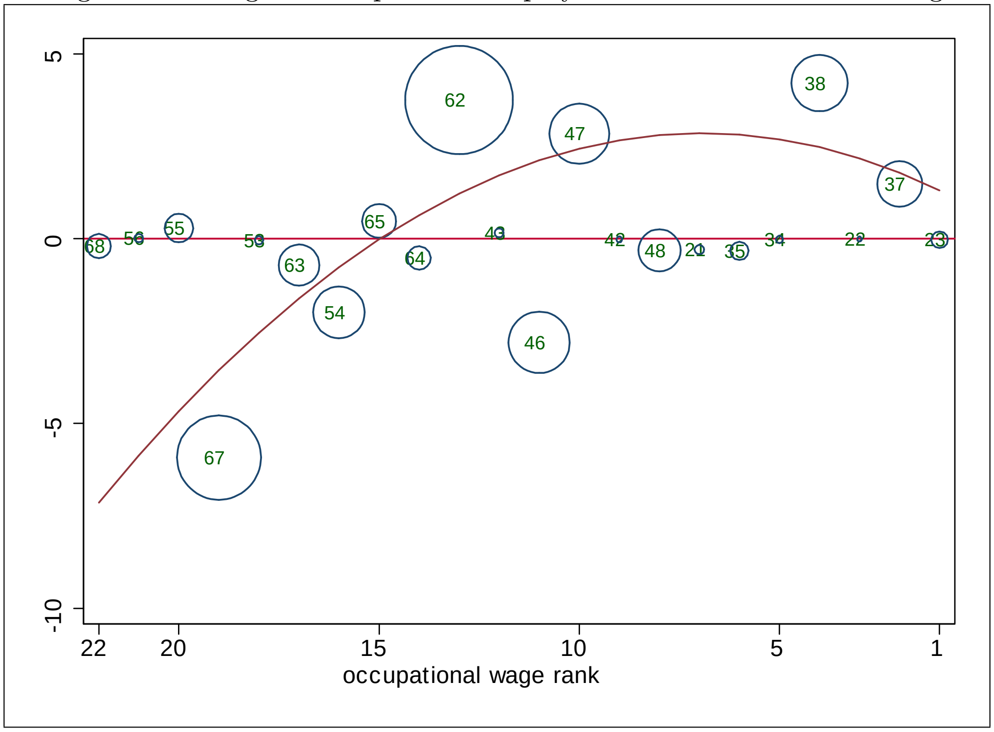
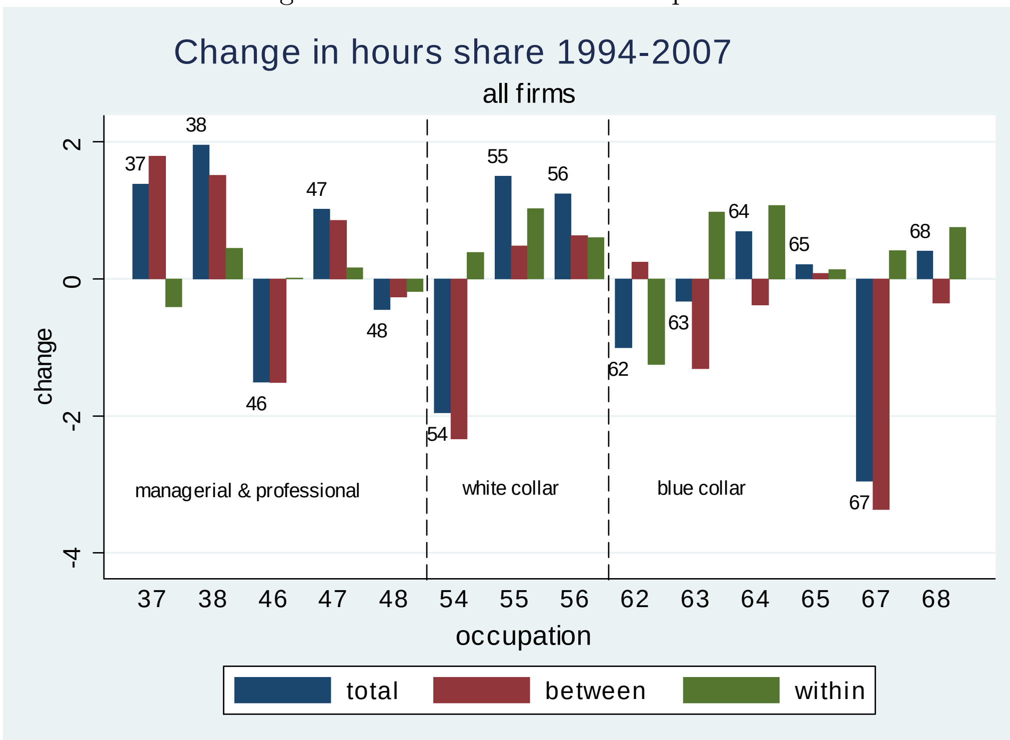


Table 3: Changes in occupational hours share: Between-Within decomposition (1994-2007)

		All firms				Nonmanufacturing				Manufacturing			
Rank	PCS2	Share	ΔShare	Between	Within	Share	ΔShare	Between	Within	Share	ΔShare	Between	Within
7	21 Small business head	0.22	-0.320	-0.278	-0.042	0.23	-0.330	-0.257	-0.072	0.21	-0.296	-0.329	0.033
3	22 Shopkeeper	0.23	-0.262	-0.118	-0.144	0.30	-0.402	-0.160	-0.242	0.05	-0.011	-0.033	0.022
1	23 Large business heads	0.67	0.038	0.127	-0.089	0.67	0.045	0.212	-0.166	0.68	-0.026	-0.122	0.096
5	34 Scientific professional	0.50	-0.122	-0.102	-0.020	0.64	-0.194	-0.132	-0.063	0.13	-0.022	-0.033	0.011
6	35 Creative professional	0.68	-0.283	-0.153	-0.129	0.64	-0.241	-0.123	-0.118	0.81	-0.333	-0.217	-0.116
2	37 Upper manager	6.91	1.384	1.791	-0.407	7.65	1.122	1.982	-0.860	4.95	1.480	1.265	0.215
4	38 Technical manager	5.75	1.954	1.511	0.443	5.07	1.394	0.687	0.707	7.59	4.211	3.704	0.507
9	42 Teacher	0.31	0.073	-0.013	0.086	0.39	0.080	-0.015	0.095	0.08	-0.020	-0.015	-0.005
12	43 Health worker	1.20	0.242	0.092	0.150	1.58	0.166	0.105	0.061	0.20	0.156	0.050	0.107
11	46 Middle manager	12.55	-1.510	-1.520	0.009	13.86	-1.396	-1.051	-0.346	9.04	-2.805	-2.714	-0.091
10	47 Technician	4.85	1.017	0.859	0.158	3.44	0.756	0.294	0.463	8.67	2.839	2.350	0.489
8	48 Foreman	2.95	-0.448	-0.265	-0.183	2.46	-0.370	-0.197	-0.173	4.25	-0.316	-0.459	0.143
18	53 Security worker	0.86	0.380	0.033	0.347	1.12	0.462	0.049	0.413	0.16	-0.043	-0.020	-0.024
16	54 Office worker	12.01	-1.954	-2.336	0.382	14.12	-2.555	-2.459	-0.096	6.43	-1.990	-2.042	0.052
20	55 Retail worker	6.85	1.499	0.477	1.022	8.68	1.408	0.668	0.740	1.96	0.285	-0.101	0.386
21	56 Personal service worker	3.98	1.240	0.635	0.605	5.41	1.272	0.863	0.409	0.18	0.013	-0.013	0.026
13	62 High Skill industrial worker	10.97	-1.002	0.245	-1.246	4.57	-0.926	-0.547	-0.379	28.05	3.748	2.255	1.493
17	63 High Skill blue collar worker	8.57	-0.329	-1.310	0.981	10.27	-0.726	-1.184	0.458	4.08	-0.716	-1.700	0.985
14	64 Driver	4.94	0.692	-0.382	1.075	6.31	0.744	-0.344	1.088	1.28	-0.523	-0.494	-0.029
15	65 Skill distribution worker	2.65	0.208	0.077	0.131	2.61	0.118	0.023	0.095	2.76	0.474	0.199	0.275
19	67 Low Skill industrial worker	8.58	-2.951	-3.359	0.407	5.34	-0.841	-2.197	1.356	17.03	-5.916	-6.367	0.451
22	68 Low Skill blue collar worker	3.73	0.401	-0.352	0.753	4.60	0.353	-0.320	0.672	1.43	-0.202	-0.479	0.277

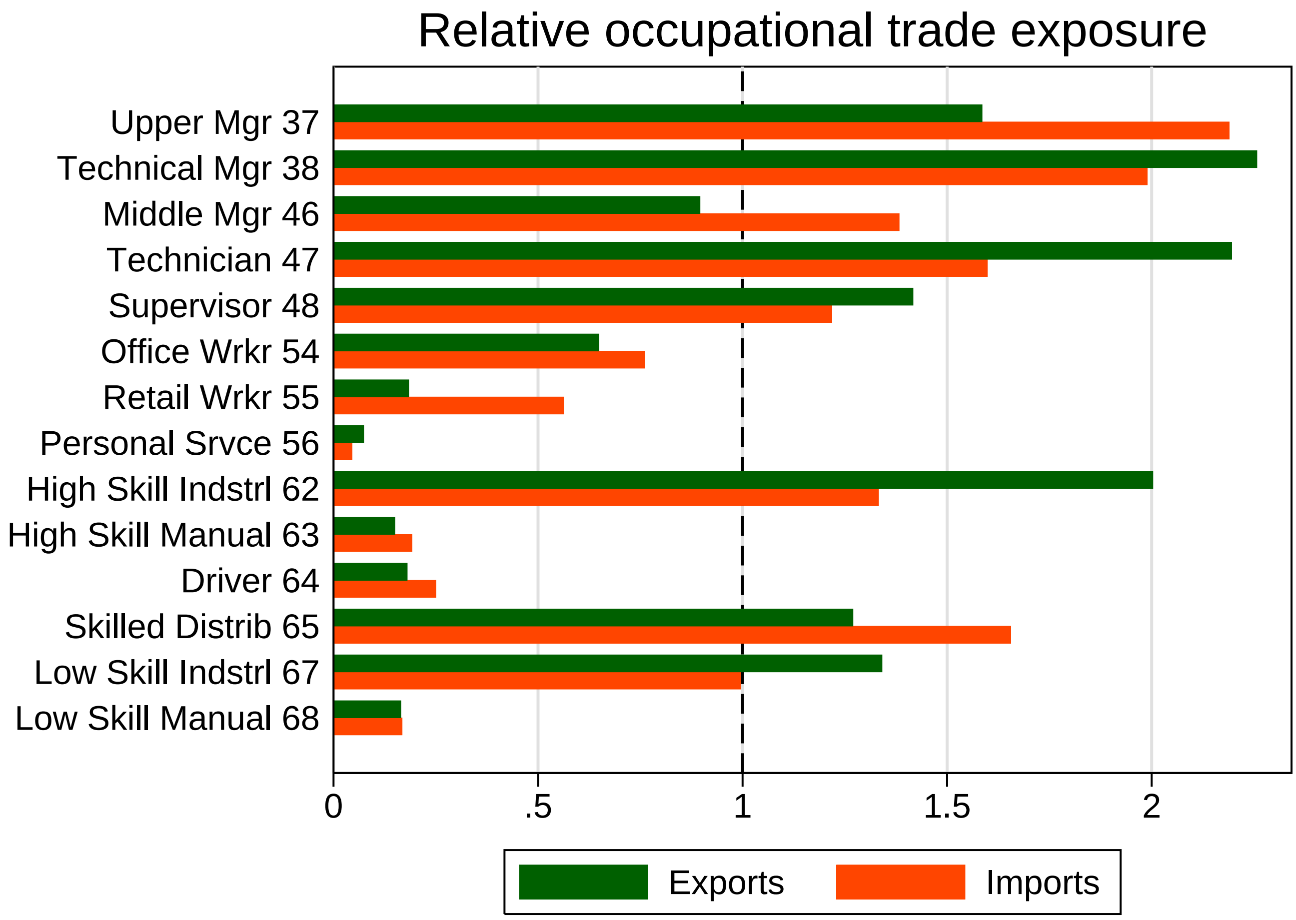
Notes: *Rank* orders PCS codes according to occupational mean wage. *Share* refers to the time average revised levels of hours shares. The 14 largest occupations are boxed.

Figure 6: Within-between decomposition



Notes to Table 3 and Figure 6: Changes in share of occupational hours worked from 1994 to 2007 are decomposed into within-firm and between-firm changes using equation (1).

Figure 7: Occupational share of trade relative to occupational share of hours



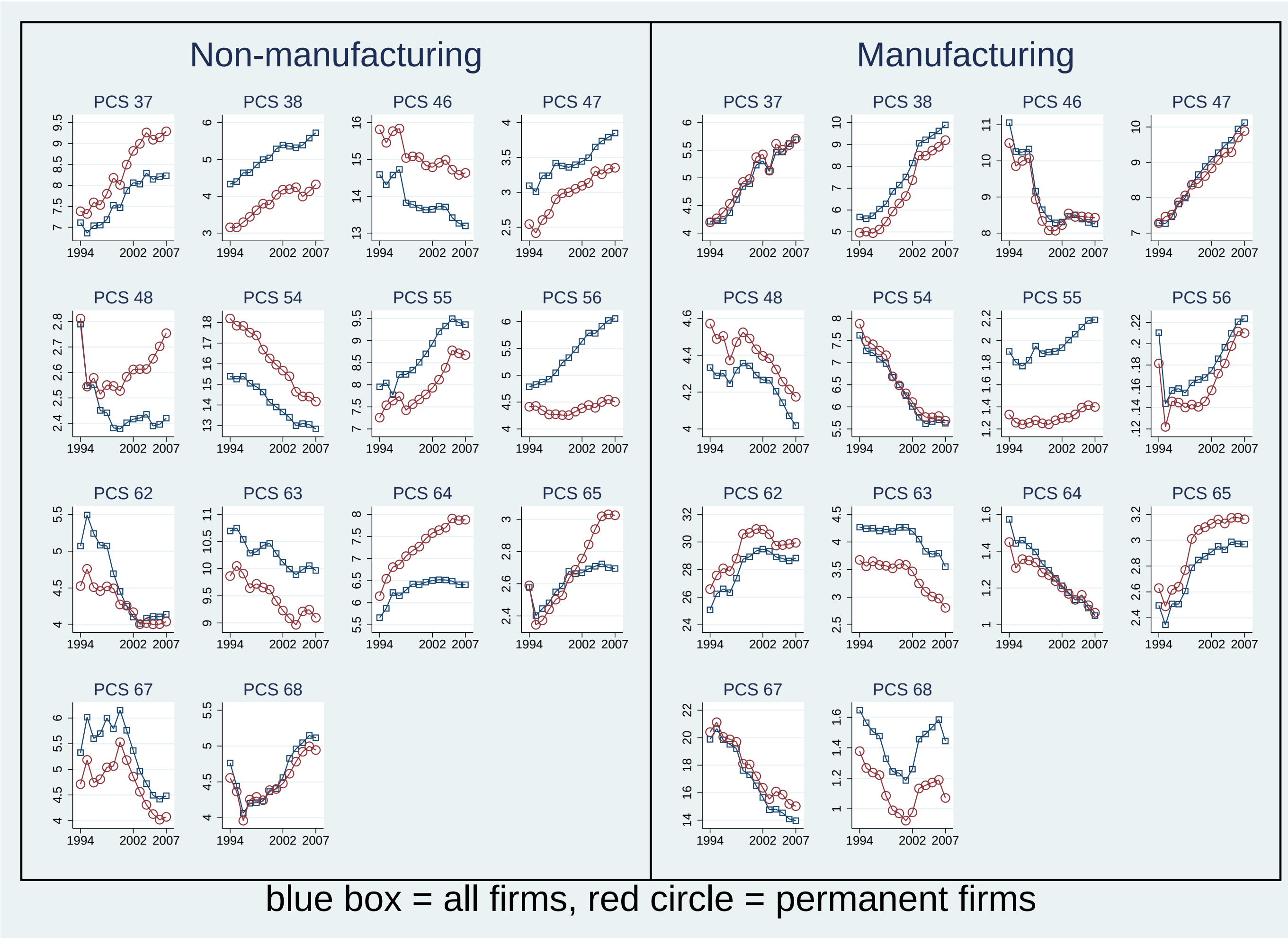
Notes to Figure 7: Occupational trade exposure defined by equation (3). Figure shows average relative exposure from 1994 to 2007.

Table 4: Economywide occupational exposure, 2002

	21	22	23	34	35	**37**	**38**	42	43	**46**	**47**	**48**	53	**54**	**55**	**56**	**62**	**63**	**64**	**65**	**67**	**68**
excluding own	0.02	0.03	0.44	0.36	0.23	**0.68**	**0.55**	0.33	0.40	**0.71**	**0.56**	**0.59**	0.31	**0.69**	**0.29**	**0.35**	**0.43**	**0.58**	**0.48**	**0.45**	**0.49**	**0.53**
including own	0.02	0.03	0.45	0.38	0.24	**0.75**	**0.60**	0.34	0.45	**0.82**	**0.61**	**0.61**	0.32	**0.88**	**0.35**	**0.39**	**0.52**	**0.65**	**0.52**	**0.47**	**0.55**	**0.57**
cross-occupational																						
21 Small business head	1.00	0.00	0.01	0.02	0.02	0.12	0.09	0.01	0.03	0.27	0.11	0.14	0.01	0.41	0.17	0.07	0.20	0.63	0.11	0.06	0.16	0.37
22 Shopkeeper	0.00	1.00	0.01	0.10	0.05	0.33	0.18	0.03	0.05	0.49	0.13	0.08	0.02	0.44	0.22	0.11	0.07	0.21	0.13	0.08	0.11	0.16
23 Large business heads	0.01	0.01	1.00	0.13	0.10	0.66	0.53	0.11	0.14	0.83	0.49	0.47	0.09	0.88	0.29	0.18	0.46	0.50	0.38	0.40	0.51	0.46
34 Scientific professional	0.12	0.19	0.42	1.00	0.38	0.84	0.60	0.61	0.84	0.86	0.59	0.65	0.41	0.91	0.34	0.57	0.40	0.74	0.53	0.36	0.40	0.57
35 Creative professional	0.01	0.07	0.37	0.36	1.00	0.76	0.53	0.56	0.49	0.88	0.55	0.56	0.34	0.81	0.26	0.57	0.39	0.60	0.47	0.29	0.38	0.45
37 Upper manager	0.02	0.04	0.56	0.45	0.27	**1.00**	**0.77**	0.39	0.46	**0.92**	**0.72**	**0.58**	0.36	**0.92**	**0.38**	**0.41**	**0.50**	**0.54**	**0.53**	**0.49**	**0.54**	**0.54**
38 Technical manager	0.00	0.02	0.61	0.36	0.17	**0.89**	**1.00**	0.34	0.37	**0.90**	**0.86**	**0.62**	0.27	**0.93**	**0.28**	**0.29**	**0.63**	**0.53**	**0.47**	**0.54**	**0.60**	**0.49**
42 Teacher	0.05	0.04	0.27	0.57	0.44	0.72	0.39	1.00	0.67	0.78	0.47	0.42	0.35	0.89	0.12	0.49	0.25	0.50	0.38	0.18	0.27	0.45
43 Health worker	0.02	0.07	0.30	0.84	0.31	0.83	0.44	0.60	1.00	0.85	0.48	0.61	0.35	0.96	0.14	0.59	0.28	0.75	0.45	0.20	0.31	0.52
46 Middle manager	0.01	0.02	0.52	0.37	0.25	**0.82**	**0.66**	0.35	0.40	**1.00**	**0.64**	**0.56**	0.32	**0.89**	**0.44**	**0.39**	**0.49**	**0.57**	**0.51**	**0.50**	**0.54**	**0.56**
47 Technician	0.01	0.03	0.57	0.37	0.18	**0.85**	**0.86**	0.37	0.44	**0.90**	**1.00**	**0.73**	0.34	**0.94**	**0.34**	**0.32**	**0.74**	**0.63**	**0.53**	**0.64**	**0.69**	**0.57**
48 Foreman	0.01	0.02	0.48	0.29	0.23	**0.79**	**0.71**	0.31	0.40	**0.86**	**0.74**	**1.00**	0.36	**0.90**	**0.30**	**0.35**	**0.71**	**0.73**	**0.60**	**0.59**	**0.71**	**0.65**
53 Security worker	0.01	0.01	0.43	0.31	0.35	0.84	0.55	0.41	0.50	0.87	0.64	0.65	1.00	0.92	0.22	0.42	0.52	0.53	0.57	0.41	0.55	0.62
54 Office worker	0.02	0.04	0.35	0.53	0.32	**0.80**	**0.52**	0.48	0.63	**0.84**	**0.58**	**0.59**	0.39	**1.00**	**0.25**	**0.46**	**0.39**	**0.61**	**0.52**	**0.32**	**0.41**	**0.56**
55 Retail worker	0.01	0.01	0.45	0.33	0.17	**0.63**	**0.41**	0.11	0.29	**0.76**	**0.40**	**0.45**	0.28	**0.70**	**1.00**	**0.30**	**0.38**	**0.68**	**0.47**	**0.52**	**0.50**	**0.54**
56 Personal service worker	0.01	0.02	0.19	0.14	0.27	**0.40**	**0.21**	0.22	0.29	**0.56**	**0.22**	**0.38**	0.18	**0.54**	**0.18**	**1.00**	**0.15**	**0.57**	**0.20**	**0.14**	**0.20**	**0.30**
62 High Skill industrial worker	0.01	0.00	0.59	0.27	0.16	**0.80**	**0.83**	0.25	0.41	**0.87**	**0.83**	**0.85**	0.33	**0.93**	**0.31**	**0.25**	**1.00**	**0.67**	**0.58**	**0.75**	**0.89**	**0.62**
63 High Skill blue collar worker	0.04	0.02	0.29	0.16	0.12	**0.41**	**0.33**	0.15	0.19	**0.54**	**0.36**	**0.46**	0.14	**0.65**	**0.29**	**0.25**	**0.35**	**1.00**	**0.33**	**0.30**	**0.37**	**0.60**
64 Driver	0.01	0.01	0.38	0.12	0.08	**0.58**	**0.52**	0.16	0.16	**0.71**	**0.36**	**0.48**	0.19	**0.83**	**0.23**	**0.16**	**0.40**	**0.54**	**1.00**	**0.53**	**0.58**	**0.48**
65 Skill distribution worker	0.00	0.01	0.63	0.39	0.28	**0.85**	**0.77**	0.35	0.44	**0.92**	**0.73**	**0.80**	0.43	**0.93**	**0.58**	**0.38**	**0.73**	**0.73**	**0.73**	**1.00**	**0.82**	**0.68**
67 Low Skill industrial worker	0.00	0.00	0.59	0.33	0.25	**0.79**	**0.77**	0.33	0.45	**0.87**	**0.76**	**0.80**	0.39	**0.92**	**0.43**	**0.38**	**0.86**	**0.66**	**0.64**	**0.74**	**1.00**	**0.65**
68 Low Skill blue collar worker	0.01	0.01	0.31	0.19	0.09	**0.55**	**0.38**	0.21	0.30	**0.62**	**0.40**	**0.50**	0.30	**0.74**	**0.24**	**0.31**	**0.41**	**0.65**	**0.41**	**0.32**	**0.45**	**1.00**

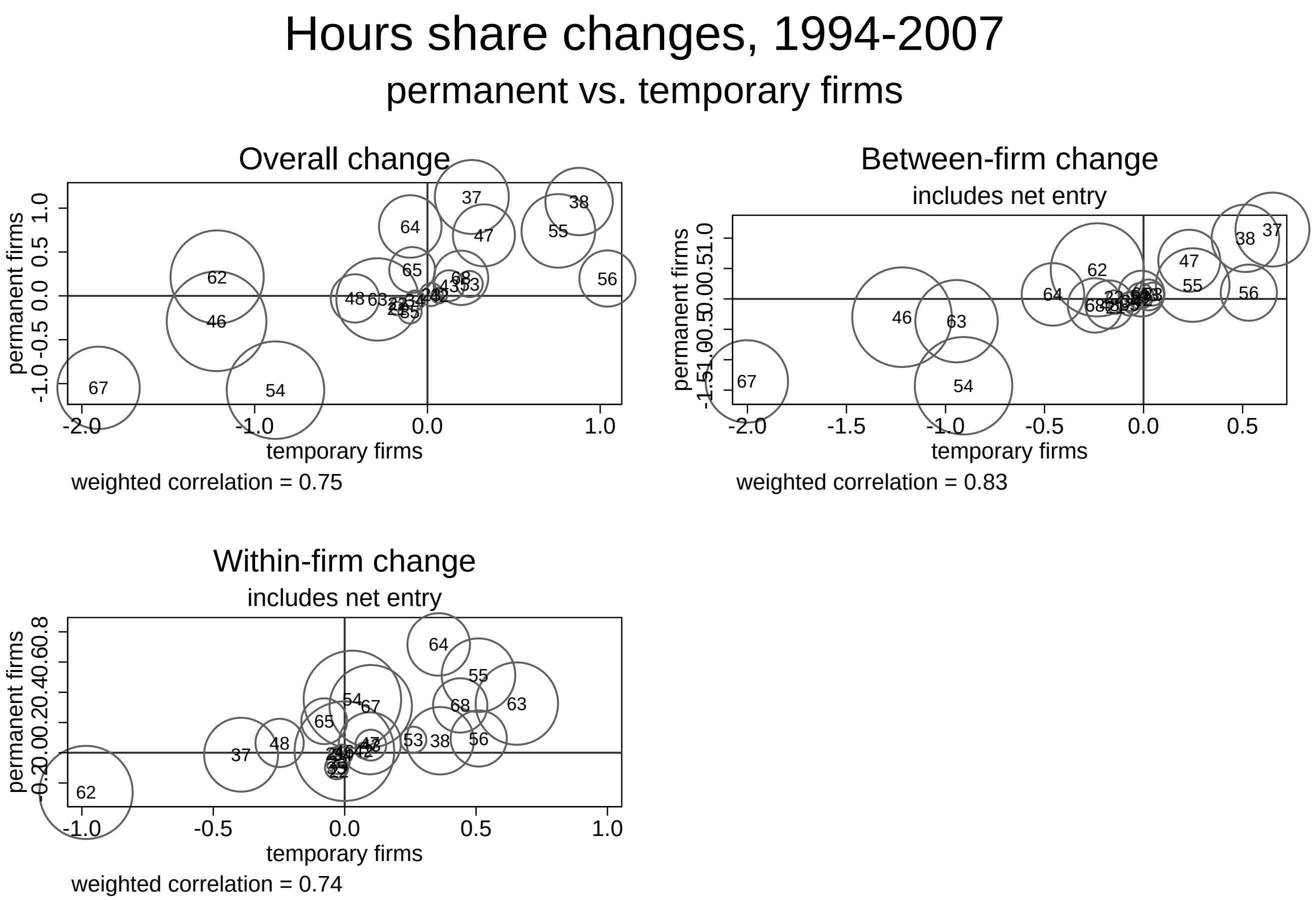
Columns give share of hours worked exposed to each occupation. An hour of work in a firm is defined as "exposed" to an occupation if the firm employs workers in that occupation. The first two rows measure economywide exposure, remaining rows report cross-occupational exposure. For example, consider the column labelled 54, Office Workers. The first number in the column, 0.69, indicates that 69 % of hours worked in the economy in occupations other than PCS 54 happen in firms that employ PCS 54. The second number, 0.88, includes exposure of office workers to themselves, indicating that 88 % of all hours worked occur in firms that employ PCS 54. Turning to the row labelled 38, the number 0.93 indicates that 93% of hours in PCS 38, Technical Managers and Engineers, are worked in firms that employ PCS 54.

Figure 8: Occupational hours shares for all firms and permanent firms



Notes to Figures 8 and 9: "Permanent" firms are those with positive hours worked for each year from 1994 to 2007, "All" includes permanent and all other firms. In Figure 9, size of circles is proportional to occupation's hours share in 2002. For key to occupations, see Tables 1 and 2.

Figure 9: Changes in occupational hours shares



Note: permanent firms active from 1994 to 2007, temporary firms all others.

Table 5: Shea first stage partial R^2

Nonmanufacturing

PCS	37	46	48	54	55	56
Techies 2002	0.669	0.657	0.699	0.657	0.640	0.744
Techies 2002 > 0	0.245	0.262	0.245	0.275	0.306	0.305
Imports 2002	0.603	0.600	0.631	0.601	0.633	0.694
Imports 2002 > 0	0.204	0.210	0.199	0.211	0.228	0.171
Exports 2002	0.550	0.560	0.572	0.556	0.573	0.587
Exports 2002 > 0	0.210	0.214	0.216	0.214	0.239	0.197
PCS	62	63	64	65	67	68
Techies 2002	0.708	0.665	0.681	0.675	0.697	0.664
Techies 2002 > 0	0.242	0.295	0.280	0.243	0.268	0.290
Imports 2002	0.630	0.626	0.642	0.623	0.622	0.642
Imports 2002 > 0	0.189	0.217	0.211	0.221	0.209	0.209
Exports 2002	0.590	0.538	0.566	0.556	0.578	0.543
Exports 2002 > 0	0.202	0.219	0.207	0.231	0.221	0.217

Manufacturing

PCS	37	46	48	54	55	56
Techies 2002	0.561	0.550	0.563	0.551	0.560	0.661
Techies 2002 > 0	0.142	0.167	0.147	0.171	0.167	0.117
Imports 2002	0.571	0.571	0.573	0.562	0.669	0.688
Imports 2002 > 0	0.131	0.136	0.126	0.140	0.112	0.071
Exports 2002	0.681	0.679	0.681	0.677	0.735	0.784
Exports 2002 > 0	0.183	0.183	0.172	0.186	0.177	0.149
PCS	62	63	64	65	67	68
Techies 2002	0.542	0.556	0.550	0.568	0.551	0.569
Techies 2002 > 0	0.168	0.171	0.180	0.142	0.169	0.174
Imports 2002	0.564	0.598	0.581	0.569	0.567	0.561
Imports 2002 > 0	0.138	0.113	0.135	0.110	0.137	0.115
Exports 2002	0.674	0.701	0.720	0.689	0.675	0.697
Exports 2002 > 0	0.185	0.165	0.204	0.164	0.184	0.157

Notes to Table 5: Reports first stage goodness of fit measure for 2SLS estimation of equation (5). Each number in the table is the adjusted Shea (1997) partial R^2 of the first stage equation for the endogenous variable listed in the row, corresponding to the second stage equation listed in the column. For key to occupations, see Tables 1 and 2.

Table 6: Shares of hours worked

	nonmanufacturing		
techies?	no	yes	Total
no trade	26.7	31.1	57.8
import only	1.9	7.4	9.3
export only	1.5	5.0	6.5
import & export	1.7	24.7	26.4
Total	31.8	68.2	100.0

	manufacturing		
techies?	no	yes	Total
no trade	6.1	7.6	13.6
import only	0.8	4.0	4.7
export only	0.9	3.2	4.1
import & export	2.0	75.5	77.5
Total	9.7	90.3	100.0

Table 7: Shares of trade

	nonmanufacturing					
	imports			exports		
techies?	no	yes	total	no	yes	total
import only	5.6	5.8	11.4	0.0	0.0	0.0
export only	0.0	0.0	0.0	4.3	4.7	8.9
import & export	14.3	74.3	88.6	11.4	79.7	91.1
Total	20.0	80.0	100.0	15.6	84.4	100.0

	manufacturing					
	imports			exports		
techies?	no	yes	total	no	yes	total
import only	0.4	1.0	1.4	0.0	0.0	0.0
export only	0.0	0.0	0.0	0.2	0.5	0.7
import & export	1.8	96.8	98.6	0.9	98.4	99.4
Total	2.1	97.9	100.0	1.1	98.9	100.0

Notes to Tables 6 and 7: These tables report cross tabs of frequencies for the estimation sample.

Notes to Tables 8 through 11: The tables on the following four pages report estimated effects derived from 2SLS estimation of equations (5) (columns labeled *overall)* and (6) (other columns). Reported effects are functions of the estimated parameters and moments of the data, as given by equations (7) and (8). Effects highlighted in yellow are statistically significantly different from zero at the 90 percent level or more.

Table 8: Effects of techies on employment shares in nonmanufacturing firms

		overall		no trade		imports & exports > 0	
		extensive	intensive	extensive	intensive	extensive	intensive
		(1)	(2)	(3)	(4)	(5)	(6)
37	Top managers and professionals	0.340	0.215	0.516	0.051	0.179	0.295
		0.182	*0.082*	*0.160*	*0.038*	*0.436*	*0.108*
46	Mid-level professionals	-0.106	0.048	-0.128	0.019	0.276	0.096
		0.096	*0.019*	*0.113*	*0.024*	*0.239*	*0.035*
48	Foremen, Supervisors	0.176	-0.067	0.074	-0.009	-0.076	-0.132
		0.181	*0.055*	*0.210*	*0.110*	*0.343*	*0.100*
54	Office workers	0.006	-0.055	-0.003	-0.028	-0.399	-0.094
		0.110	*0.030*	*0.132*	*0.033*	*0.284*	*0.066*
55	Retail workers	0.120	-0.153	0.066	0.002	-0.030	-0.251
		0.319	*0.076*	*0.372*	*0.060*	*0.714*	*0.145*
56	Personal service workers	-0.616	0.130	-0.319	0.161	-3.570	0.014
		0.875	*0.078*	*0.984*	*0.153*	*2.294*	*0.157*
62	Skilled industrial workers	1.458	-0.261	1.430	0.275	0.787	-0.401
		0.596	*0.213*	*0.433*	*0.162*	*1.621*	*0.169*
63	Skilled manual laborers	0.214	-0.062	0.181	0.025	0.263	-0.095
		0.177	*0.051*	*0.166*	*0.102*	*0.756*	*0.063*
64	Drivers	-0.080	-0.132	-0.108	-0.288	0.254	-0.061
		0.246	*0.057*	*0.327*	*0.150*	*0.668*	*0.065*
65	Skilled transport workers	0.420	-0.161	0.689	-0.137	-0.224	-0.123
		0.280	*0.044*	*0.386*	*0.090*	*0.635*	*0.052*
67	Low skill industrial workers	0.220	0.154	0.525	0.100	-1.060	0.218
		0.261	*0.066*	*0.354*	*0.092*	*0.524*	*0.088*
68	Low skill manual laborers	-0.673	-0.199	-0.712	-0.156	0.095	-0.230
		0.241	*0.079*	*0.293*	*0.086*	*0.115*	*0.121*

Standard errors italicized.

Table 9: Effects of techies on employment shares in manufacturing firms

		overall		no trade		imports & exports > 0	
		extensive	intensive	extensive	intensive	extensive	intensive
		(1)	(2)	(3)	(4)	(5)	(6)
37	Top managers and professionals	0.211	0.073	0.832	-0.206	-0.123	0.204
		0.219	*0.058*	*0.304*	*0.225*	*0.382*	*0.135*
46	Mid-level professionals	0.563	0.324	0.539	0.259	0.636	0.301
		0.196	*0.156*	*0.260*	*0.203*	*0.306*	*0.178*
48	Foremen, Supervisors	-0.465	-0.134	-0.899	0.180	-0.011	-0.170
		0.583	*0.059*	*1.084*	*0.639*	*0.249*	*0.063*
54	Office workers	-0.511	-0.163	-0.528	0.399	-0.874	-0.175
		0.194	*0.217*	*0.341*	*0.348*	*0.306*	*0.215*
55	Retail workers	-9.606	0.523	-6.980	7.270	4.340	-0.078
		7.976	*0.669*	*5.857*	*5.952*	*5.264*	*0.689*
56	Personal service workers	-4.688	-1.540	6.880	-2.930	-24.300	-1.270
		6.616	*1.375*	*8.644*	*6.387*	*7.807*	*1.288*
62	Skilled industrial workers	-0.822	-0.163	-1.270	0.256	0.015	-0.216
		0.347	*0.080*	*0.432*	*0.266*	*0.215*	*0.075*
63	Skilled manual laborers	0.601	-0.030	2.560	-2.670	-2.910	0.099
		1.210	*0.203*	*1.078*	*0.831*	*1.709*	*0.227*
64	Drivers	1.520	0.254	2.380	-1.390	0.670	0.266
		0.556	*0.087*	*0.864*	*0.739*	*0.863*	*0.092*
65	Skilled transport workers	-1.108	0.148	-1.310	0.446	-0.637	0.110
		0.598	*0.096*	*0.943*	*0.358*	*0.446*	*0.099*
67	Low skill industrial workers	1.133	0.035	1.540	-0.623	0.086	0.126
		0.753	*0.105*	*0.924*	*0.495*	*0.340*	*0.074*
68	Low skill manual laborers	1.962	0.444	2.900	1.310	0.582	0.388
		0.418	*0.106*	*0.539*	*0.434*	*0.672*	*0.104*

Standard errors italicized.

Table 10: Effects of trade on employment shares in nonmanufacturing firms

		imports				exports			
		overall		techies > 0		overall		techies > 0	
		extensive	intensive	extensive	intensive	extensive	intensive	extensive	intensive
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
37	Top managers and professionals	0.182	0.023	-0.026	0.018	0.054	0.018	-0.060	0.010
		0.263	*0.010*	*0.275*	*0.018*	*0.242*	*0.008*	*0.286*	*0.007*
46	Mid-level professionals	0.161	-0.010	0.035	-0.010	0.077	-0.001	0.159	0.003
		0.111	*0.006*	*0.164*	*0.010*	*0.146*	*0.002*	*0.200*	*0.003*
48	Foremen, Supervisors	0.473	0.000	0.635	0.001	-0.761	0.001	-0.771	0.003
		0.295	*0.009*	*0.357*	*0.012*	*0.285*	*0.005*	*0.350*	*0.004*
54	Office workers	0.062	0.010	0.331	-0.002	-0.604	0.006	-0.822	0.006
		0.165	*0.009*	*0.276*	*0.011*	*0.219*	*0.002*	*0.329*	*0.003*
55	Retail workers	-0.385	0.036	-0.531	0.081	0.417	-0.003	0.664	-0.009
		0.245	*0.020*	*0.374*	*0.042*	*0.301*	*0.004*	*0.388*	*0.006*
56	Personal service workers	-1.058	-0.002	-1.280	-0.001	-0.479	0.006	-0.244	0.001
		0.747	*0.011*	*0.909*	*0.016*	*1.130*	*0.006*	*1.129*	*0.006*
62	Skilled industrial workers	-0.957	0.010	-0.802	0.003	-0.201	-0.044	0.199	-0.022
		0.660	*0.029*	*0.625*	*0.030*	*0.521*	*0.022*	*0.580*	*0.016*
63	Skilled manual laborers	0.055	-0.019	0.184	-0.009	-0.100	-0.002	-0.196	-0.005
		0.224	*0.011*	*0.269*	*0.012*	*0.201*	*0.003*	*0.276*	*0.003*
64	Drivers	0.902	-0.033	1.240	-0.040	-0.002	-0.002	-0.451	-0.003
		0.490	*0.012*	*0.729*	*0.015*	*0.447*	*0.003*	*0.628*	*0.005*
65	Skilled transport workers	-0.060	-0.065	-0.164	-0.058	0.483	-0.005	0.496	-0.003
		0.309	*0.021*	*0.448*	*0.026*	*0.297*	*0.005*	*0.405*	*0.007*
67	Low skill industrial workers	0.009	0.014	0.032	0.033	-0.335	-0.004	-0.480	-0.011
		0.287	*0.017*	*0.369*	*0.023*	*0.403*	*0.007*	*0.521*	*0.010*
68	Low skill manual laborers	-1.220	-0.013	-2.100	-0.018	2.410	-0.018	3.387	-0.016
		0.839	*0.012*	*1.301*	*0.015*	*1.074*	*0.007*	*1.563*	*0.008*

Standard errors italicized.

Table 11: Effects of trade on employment shares in manufacturing firms

		imports				exports			
		overall		techies > 0		overall		techies > 0	
		extensive	intensive	extensive	intensive	extensive	intensive	extensive	intensive
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
37	Top managers and professionals	0.112	0.000	0.031	0.036	0.413	-0.002	0.333	-0.035
		0.223	*0.011*	*0.307*	*0.044*	*0.185*	*0.002*	*0.238*	*0.055*
46	Mid-level professionals	0.187	-0.012	0.028	0.000	-0.068	-0.002	0.085	-0.040
		0.327	*0.061*	*0.418*	*0.066*	*0.261*	*0.062*	*0.354*	*0.055*
48	Foremen, Supervisors	0.485	0.021	0.650	0.030	-0.053	-0.010	-0.117	-0.008
		0.286	*0.025*	*0.417*	*0.026*	*0.272*	*0.034*	*0.272*	*0.038*
54	Office workers	-0.162	0.062	-0.231	0.025	0.103	-0.039	0.180	-0.008
		0.307	*0.041*	*0.469*	*0.041*	*0.253*	*0.075*	*0.367*	*0.044*
55	Retail workers	13.132	-0.394	3.510	-0.520	-7.502	-0.646	-1.670	-0.695
		15.526	*0.479*	*5.570*	*0.464*	*8.066*	*0.664*	*3.300*	*0.659*
56	Personal service workers	-7.693	0.327	-13.300	0.255	3.552	0.193	5.673	0.106
		5.361	*0.288*	*11.249*	*0.250*	*2.890*	*0.482*	*8.130*	*0.340*
62	Skilled industrial workers	1.250	-0.016	1.530	-0.002	-1.013	0.139	-1.158	0.153
		0.752	*0.031*	*0.835*	*0.038*	*0.546*	*0.097*	*0.627*	*0.097*
63	Skilled manual laborers	6.196	0.064	4.460	0.132	-3.435	0.208	-2.687	0.273
		2.536	*0.190*	*2.264*	*0.211*	*1.795*	*0.234*	*1.755*	*0.233*
64	Drivers	0.941	-0.054	0.606	-0.063	-0.317	0.145	-0.145	0.139
		0.546	*0.051*	*0.726*	*0.060*	*0.500*	*0.060*	*0.624*	*0.069*
65	Skilled transport workers	2.054	0.033	1.390	0.026	-1.070	-0.001	-0.572	-0.012
		1.134	*0.045*	*0.806*	*0.054*	*0.727*	*0.076*	*0.466*	*0.090*
67	Low skill industrial workers	-3.255	-0.015	-3.620	-0.048	2.106	-0.178	2.451	-0.230
		1.668	*0.053*	*1.852*	*0.068*	*1.186*	*0.170*	*1.369*	*0.174*
68	Low skill manual laborers	0.071	0.046	-0.210	0.027	-0.558	-0.119	-0.804	-0.037
		0.573	*0.039*	*0.727*	*0.041*	*0.577*	*0.053*	*0.749*	*0.034*

Standard errors italicized.

Table 12: Shea first stage partial R^2 for baseline employment growth regressions

	Nonmanufacturing	Manufacturing
Techies 2002	0.584	0.513
Techies 2002 > 0	0.209	0.152
Imports 2002	0.568	0.561
Imports 2002 > 0	0.219	0.142
Exports 2002	0.542	0.671
Exports 2002 > 0	0.222	0.175

Notes to Table 12: Reports first stage goodness of fit measure for 2SLS estimation of equation (9). Each number in the table is the adjusted Shea (1997) partial R^2 of the first stage equation for the endogenous variable listed in the row, corresponding to the second stage equation listed in the column.

Table 13: Effects of techies (Panel A) and trade (Panel B) on employment growth rates

	overall		no trade		imports & exports	
	extensive	intensive	extensive	intensive	extensive	intensive
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Nonmanufacturing	0.344	0.011	0.311	0.153	0.244	-0.148
	0.189	*0.043*	*0.179*	*0.059*	*0.305*	*0.088*
Manufacturing	0.939	0.219	1.140	0.134	0.392	0.264
	0.211	*0.067*	*0.211*	*0.146*	*0.291*	*0.080*

	imports				exports			
	overall		techies		overall		techies	
	extensive	intensive	extensive	intensive	extensive	intensive	extensive	intensive
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nonmanufacturing	-0.126	0.002	-0.090	0.008	-0.339	-0.005	-0.279	-0.010
	0.218	*0.009*	*0.372*	*0.014*	*0.218*	*0.005*	*0.373*	*0.003*
Manufacturing	-0.148	0.036	-0.207	0.043	0.077	-0.038	0.025	0.003
	0.268	*0.039*	*0.339*	*0.044*	*0.212*	*0.051*	*0.280*	*0.050*

Standard errors italicized.

Table 14: Effects of techies, exports and different classes of imports

A. Nonmanufacturing

	extensive (1)	intensive (2)	extensive (3)	intensive (4)	extensive (5)	intensive (6)
techies	0.344	0.011	0.331	0.011	0.400	0.015
	0.189	*0.043*	*0.203*	*0.042*	*0.180*	*0.040*
exports	-0.339	-0.005	-0.390	-0.005	-0.179	-0.005
	0.218	*0.005*	*0.220*	*0.004*	*0.245*	*0.005*
imports	-0.126	0.002	-0.040	0.010		
	0.218	*0.009*	*0.330*	*0.010*		
imports of intermediate inputs			0.012	-0.012		
			0.308	*0.006*		
imports from China					-0.146	0.005
					0.445	*0.006*
imports from high income countries					0.031	0.008
					0.257	*0.010*
imports from other countries					-0.373	0.001
					0.357	*0.004*

B. Manufacturing

	extensive (1)	intensive (2)	extensive (3)	intensive (4)	extensive (5)	intensive (6)
techies	0.939	0.219	0.929	0.221	0.815	0.229
	0.211	*0.067*	*0.209*	*0.067*	*0.210*	*0.069*
exports	0.077	-0.038	0.055	-0.031	0.182	-0.020
	0.212	*0.051*	*0.213*	*0.051*	*0.200*	*0.050*
imports	-0.148	0.036	0.698	0.066		
	0.268	*0.039*	*0.518*	*0.057*		
imports of intermediate inputs			-0.815	-0.032		
			0.375	*0.046*		
imports from China					-0.085	0.006
					0.188	*0.005*
imports from high income countries					-0.010	0.098
					0.227	*0.049*
imports from other countries					-0.431	-0.025
					0.211	*0.011*

Standard errors italicized.

Table 15: Second stage goodness of fit and test statistics, baseline within regressions

Nonmanufacturing

PCS	37	46	48	54	55	56
Goodness of fit						
Weighted R^2	0.052	0.017	0.022	0.034	0.017	0.020
Explained within	-2.827	-0.714	0.066	2.410	0.346	-0.664
p-values						
Joint significance, $\chi^2(6)$	0.000	0.029	0.161	0.000	0.040	0.044
Endogeneity, $\chi^2(6)$	0.000	0.000	0.000	0.000	0.000	0.000
Overid, $\chi^2(24)$	0.000	0.000	0.000	0.000	0.000	0.000
PCS	62	63	64	65	67	68
Goodness of fit						
Weighted R^2	0.035	0.003	0.017	0.033	0.050	0.033
Explained within	8.162	0.669	-0.136	0.560	1.834	0.158
p-values						
Joint significance, $\chi^2(6)$	0.244	0.005	0.111	0.000	0.061	0.015
Endogeneity, $\chi^2(6)$	0.000	0.000	0.000	0.000	0.000	0.000
Overid, $\chi^2(24)$	0.000	0.000	0.000	0.000	0.000	0.000

Manufacturing

PCS	37	46	48	54	55	56
Goodness of fit						
Weighted R^2	0.067	0.035	0.015	0.030	0.020	0.015
Explained within	-17.185	0.249	0.100	-0.798	0.646	0.287
p-values						
Joint significance, $\chi^2(6)$	0.000	0.000	0.017	0.000	0.012	0.021
Endogeneity, $\chi^2(6)$	0.000	0.000	0.000	0.000	0.000	0.715
Overid, $\chi^2(24)$	0.000	0.000	0.038	0.000	0.025	0.808
PCS	62	63	64	65	67	68
Goodness of fit						
Weighted R^2	0.176	0.064	0.013	0.121	0.376	0.011
Explained within	-0.096	1.277	-24.195	-0.618	0.788	2.862
p-values						
Joint significance, $\chi^2(6)$	0.000	0.000	0.000	0.086	0.000	0.000
Endogeneity, $\chi^2(6)$	0.000	0.000	0.001	0.000	0.000	0.139
Overid, $\chi^2(24)$	0.000	0.000	0.990	0.000	0.000	0.057

Notes to Table 15: Statistics based on 2SLS estimates of equation (5).

Table 16: Second stage goodness of fit and test statistics for baseline employment growth regressions

	Nonmanufacturing	Manufacturing
Goodness of fit		
Weighted R^2	0.006	0.039
Explained between by PCS:		
37	0.687	-0.410
46	-1.733	0.238
48	-3.896	0.216
54	-0.957	0.121
55	1.232	0.026
56	0.448	-0.053
62	9.074	0.451
63	-1.695	0.016
64	-3.075	-0.006
65	1.805	-1.159
67	-0.186	0.117
68	1.330	0.013
p-values		
Joint significance, $\chi^2(7)$	0.0086	0.000
Endogeneity, $\chi^2(7)$	0.000	0.000
Overid, $\chi^2(21)$	0.000	0.000

Notes to Table 16: Statistics based on 2SLS estimates of equation (9).