NBER WORKING PAPER SERIES

THE MARCH OF THE TECHIES: TECHNOLOGY, TRADE, AND JOB POLARIZATION IN FRANCE, 1994-2007

James Harrigan
Ariell Reshef
Farid Toubal

Working Paper 22110
http://www.nber.org/papers/w22110

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2016

This paper was begun while James Harrigan was a visiting professor in the Department of Economics at Sciences Po in 2012-2013. We thank the Bankard Fund for Political Economy at the University of Virginia, the Research in Paris fund of the Mairie de Paris, Sciences Po, and the iCODE Institute (Idex Paris-Saclay) for support. This research is also supported by a public grant overseen by the French National Research Agency (ANR) as part of the Investissements d'avenir" program (ANR-10-EQPX-17 – Centre d'accès sécurisé aux données – CASD). We thank Francis Kramarz for guidance with the data, David Autor for an insightful conference discussion, and seminar audiences in Amsterdam, Barcelona, Bloomington, Cambridge MA, Lausanne, New York, Oslo, Palo Alto, Paris, San Francisco, Stockholm, Utrecht, and West Lafayette for helpful comments. Abiy Teshome provided excellent research assistance. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

The March of the Techies: Technology, Trade, and Job Polarization in France, 1994-2007
James Harrigan, Ariell Reshef, and Farid Toubal
NBER Working Paper No. 22110
March 2016
JEL No. D3,F1,F16,F66,J2,O3

ABSTRACT

Using administrative employee-firm-level data on the entire private sector from 1994 to 2007, we show that the labor market in France has 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 among the first to analyze polarization in any country using firm-level data, and we show how polarization occured within firms, but mostly due to changes in the composition of firms (between firms). Motivated by the fact that technology adoption is mediated by technically qualified managers and technicians, we use a new measure of the propensity of a firm to adopt new technology: its 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, and grew faster, from 2002 to 2007. Offshoring reduced employment growth. Among blue-collar workers in manufacturing, importing caused skill upgrading while exporting caused skill downgrading. 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 conclude that technological change, mediated through techies, is an important cause of polarization in France. Firm-level trade had important effects in manufacturing.

James Harrigan
Department of Economics
University of Virginia
P.O. Box 400182
Charlottesville, VA 22904-4182
and NBER
harrigan@nber.org

Farid Toubal
Ecole Normale Supérieure de Cachan,
Bureau 503, Bat Cournot
61, avenue du Président Wilson
94235 Cachan Cedex, FRANCE
and Paris School of Economics, and CEPII
ftoubal@ens-cachan.fr

Ariell Reshef
Université Paris 1 - Panthéon Sorbonne
Maison des Sciences Economiques
Bureau 310
106-112 Boulevard de l'Hopital
75647 Paris Cedex 13
France
and Paris School of Economics
ariell.reshef@psemail.eu

A data appendix is available at http://www.nber.org/data-appendix/w22110

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 among 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 share composition 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 many 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 fell; 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 very 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 any of the drop in employment in office workers, where changes in firm size composition dominate. For the latter, this implies that employment growth in firms that are intensive in office workers lags behind other firms. Changes in composition also explain virtually all of the change in employment shares of managers (both top and mid-level) and of unskilled industrial workers. We are the first to document wide dispersion across occupations in the exposure of workers to imports, exports and technology (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. While the effect of technology is pervasive, trade plays an important role only in manufacturing. Within nonmanufacturing 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 of office workers. At the same time, technology causes significant skill *downgrading* among blue collar workers.

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

[3] This is consistent 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.

Trade affects the occupational mix, but mainly in manufacturing. Importing causes strong skill *upgrading*: employment shares of skilled industrial and manual laborers increase, while the 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 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 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, to a lesser extent, in Canada.[4] These findings contribute to the external validity of our work.[5] Our findings indicate the pervasiveness of job polarization: we observe a similar pattern of changes in employment shares in France as in the U.S. and the U.K., despite large differences in the way the wage distribution has evolved.

[4] In recent work Bozio, Breda, and Guillot (2016) document a similar increase in relative labor costs (including employer contributions, as opposed to net or gross wages) in France as in the U.K. and other similar economies (although still less than in the U.S.). They also estimate similar responses of relative labor costs to demand shifts as in the U.S.

[5] 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.

1.1 Relationship to existing literature

Our work contributes to the literature that documents the pervasiveness of job polarization, and studies its causes. It is distinguished by the quality of the administrative data, its comprehensiveness (the entire French private sector), our focus on within and between firm changes, and by causal inference. The 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 (which are typically based on individual employee reporting). The within-function skill dimension is absent in previous work on polarization.

This is the first paper to describe that both analyzes polarization across and within firms and makes causal inference at this disaggregate level. Since employment decisions are made at the firm level, firm-level data is ideal for studying polarization. In contrast, Beaudry, Doms, and Lewis (2010) and Autor and Dorn (2013) exploit geographical variation across local labor markets within the U.S., and Michaels, Natraj, and Van Reenen (2014) exploit variation across industries within countries.[6] Goos, Manning, and Salomons (2014) address the roles of both within-industry changes and changes in industrial composition. While they are successful in explaining the contribution of changes in industrial composition to polarization, they are less successful 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.

Industry level analysis masks substantial variation across firms. The importance of firms in explaining relative demand shifts can be illustrated by juxtaposing Berman, Bound, and Griliches (1994) with 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 size composition explains most (60%) of the increase in their wage bill share in this period. This led to opposing conclusions about the relative roles of trade versus technology in driving the same relative demand shift.

[6] 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). 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.

We are aware of only a few other papers that study polarization using comprehensive matched worker-firm data.[7] The closest paper to ours is Kerr, Maczuskij, and Maliranta (2015), who study polarization in Finland in 2000–2009. As we do, they decompose changes in occupational employment shares into within and between-firm changes. For a subset of their sample they match both trade and technology indicators at the firm level. When analyzing the effects of trade and technology on polarization, Kerr *et al* instrument for firm level trade (as we do), but are not able to address the endogeneity of their technology measures. Böckerman, Laaksonen, and Vainiomäki (2013) also analyzes Fnnish firm-level data, and find eveidence of within-frm polarization, but due to the absence of strong instruments are not able to make causal statements.

Keller and Utar (2015) analyze polarization within the Danish textile and apparel sector. Although they use firm level data, they do not exploit the firm level dimension in their analysis. Using a sample of workers employed in the sector in 1999, they 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 Denmark 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 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".

[7] Cortes and Salvatori (2015) document a large increase in the proportion of workplaces that specialize in non-routine tasks in the United Kingdom. Changes in industry composition plays a minor role in this. But because Cortes and Salvatori (2015) cannot track establishments over time, they cannot make statements about the role establishment composition versus within-establishment changes.

[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.

A second force that could help explain job polarization is offshoring, where domestic labor is replaced by labor abroad (see among many others Feenstra and Hanson (1996), Grossman and Rossi-Hansberg (2008), Rodriguez-Clare (2010), Blinder and Krueger (2013)). Our results suggest a modest role for offshoring in explaining polarization, for the simple reason that polarization is concentrated in the non-manufacturing sector where offshoring is rare. 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 immigrants find employment, at least initially; however, Oesch (2013) dismisses this as an important factor.

An important 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* affect aggregate labor demand measured in hours —which is our unit of analysis—and in fact, they probably didn't. The 35-hour regulations were designed to share the existing demand 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 (*qualifié* and *non-qualifié*, respectively). Concurrently, employment in high-skill administrative jobs declines. Maurin and

[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.

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 and use lagged initial conditions as instruments that help identify the propensitiy of local labor markets to respond to technological change. Michaels, Natraj, and Van Reenen (2014) estimate "long differences" specifications and exploit variation across industries (within countries), and instrument for differences in ICT intensity by using intial conditions in the United States. Goos, Manning, and Salomons (2014) do not 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. The firm level lends itself more naturally to studying and identifying the mechanisms of adjustment. 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 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.

[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).

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.

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 in 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.

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.

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.

[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).

In Section 4 we present a simple model of firm-level technology which is used to motivate the econometric analysis in Section 6. 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. During most of our sample France was governed by the center-right.[13] 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 and details about data definitions and matching of firms. For compactness of the exposition, we relegate additional important details to the 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 that our data includes all private sector French workers except the self-employed.[14] Our unit of analysis is annual hours paid in a firm, by occupation.[15] For each worker, the DADS reports gross and net wages, hours paid, occupation, tenure, gender and age. There is no information about workers' education or overall labor market experience. The data do 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,

[13] The Socialist President Francois Mitterand left office in Spring 1995 with a National Assembly controlled by the center-right government of prime minister Édouard Balladur until 1997. During 1997–2002 prime minister Lionel Jospin's left-wing government cohabitated with right-wing president Jacques Chirac. During 2002–2007, both the presidency and government in France were of the center-right.

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

[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.

our measure of labor input is annual firm-level hours paid 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 by occupation, average wages, etc.

From 1994 to 2007, 2.9 million private sector firms appear in our DADS Poste data.[17] These firms range in size from tiny cafes and *tabacs* to giant industrial enterprises and retailers. Our descriptive analysis includes all 2.9 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 paid in nonmanufacturing. Though these firms represent about 11 percent of firms in our sample, they are much larger than the average firm, and account for about half of aggregate hours in each year. The share of nonmanufacturing hours within the "permanent" firms is only one percent point smaller than in the larger sample.[18] Changes in occupational shares within "permanent" firms are also very similar to the larger sample (we discuss this in more detail below in Section 5.2).

2.2 Occupations: the PCS

Every job in the DADS is categorized by a two digit PCS occupation code.[19] Excluding agricultural and public sector categories, the PCS has 22 occupational categories, listed in Table 1.[20] These 22 categories are consistently defined over our period of analysis.[21] 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, and which together comprise 95 percent of hours.

Each two digit PCS category is an aggregate of as many as 40 four digit subcategories. Although hours 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 "non-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

[17] 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 457,958 other SIRENs in the DADS Poste, including public sector enterprises and nonprofits.

[18] See detailed information in the appendix.

[19] PCS stands for *Professions et Catégories Socioprofessionnelles*.

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

[21] There are some small discontinuities in how workers are assigned to occupations between 2001 and 2002, due to improvements in data processing in 2002. See the appendix for more details and for a description of how we cope with this issue.

unskilled manual laborers (PCS 63 and 68), whose jobs include gardening, cooking, repair, building trades, and cleaning. In 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 64) 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".[22] As is clear from the detailed descriptions in Table 2, many workers in these categories are closely connected with the installation, management, maintenance, and support of information and communications technology (ICT) and other new technologies. These are jobs that require technical training, skill, and experience, so we refer to workers in these two occupations as "techies". Our hypothesis is that techies mediate the adoption of new technology within firms: they are the ones who plan, purchase, and install new technology, and who train and support other workers in the use of new technology. In short, if a firm invests in new technology, 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 increasing their permanent staff of techies. However, only 0.7% of techie hours are in the IT consulting sector, which implies that almost all of the hourly services supplied by techies are obtained in-house rather than purchased from consultants.[23]

2.3 Matched firm-trade

Our source for firm-level trade data is the French Customs.[24] 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

[22] A precise definition of these categories of workers is given in the appendix.

[23] We refer to the IT consulting sector as industry code 72 in the NAF classification, which includes the following subcategories: 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.

[24] The appendix gives the details about the match between the French Customs and the DADS Poste datasets.

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 together in the same firm, with particular attention to employees working in firms with techies.

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

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

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 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 38) 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.[25] 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) 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.[26]

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

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

[26] To see this, notice that the scale of Panel A of Figure 1 in Autor and Dorn (2013) is "100 × 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.

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) shrank.

3.1.1 Polarization within and between firms

We turn next to a more detailed analysis of the changes in hours shares just described: did they occur due to within-firm adjustment, changes in firm size, or both? The change in S_{ot}, the share of hours in occupation o in the economy, can be decomposed into changes within and between firms as follows:

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

where λ_{ft} is firm f's share of economywide hours, s_{fot} is the share of occupation o in firm f, and 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. The results of this decomposition 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 hours actually being added within firms, +0.4pp. Putting these two facts together implies that firms intensive in skilled industrial workers grew, but within these firms there was substitution of unskilled for skilled industrial workers. Firms intensive in low skill industrial workers in PCS 67 exhibit disproportionately low employment growth.

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.

3.1.2 Polarization and firm entry/exit

As noted above, entry and exit of firms is accounted for by changes in the firm employment shares λ_{ft} from zero to positive or from positive to zero in equation (1). The subset of firms that have positive hours in every year from 1994 to 2007, which we call "permanent" firms, account for about half of total hours in each year. The other half of hours are accounted for by firms that enter and/or exit between 1994 and 2007. Here we focus on the contribution of net entry by these other firms to the overall changes in occupational hours shares. Letting the set of permanent firms be denoted by P and the set of other firms as O, the decomposition in (1) can be re-written as

$$\Delta S_{ot} = \underbrace{\sum_{f\in P} \Delta\lambda_{ft}\bar{s}_{fo}}_{between\ P} + \underbrace{\sum_{f\in P} \bar{\lambda}_f \Delta s_{fot}}_{within\ P} + \underbrace{\sum_{f\in O} \Delta\lambda_{ft}\bar{s}_{fo} + \sum_{f\in O} \bar{\lambda}_f \Delta s_{fot}}_{net\ entry}. \tag{2}$$

Table 4 reports the results of the decomposition in (2), separately for nonmanufacturing and manufacturing firms.[27] Column 6 of the Table shows that in most cases the contribution of net entry is the same sign as the overall change. In a few occupations (Personal Service Workers in nonmanufacturing and Supervisors in manufacturing) net entry accounts for the bulk of the overall change. The overall skill upgrading of industrial workers in manufacturing, as seen by growth in the share of skilled industrial workers (+3.8pp, PCS 62) and a drop in the share of the unskilled (-5.9pp, PCS 67), is driven by a combination of an increase in skill intensity both within and between permanent firms combined with substantial net exit of firms intensive in unskilled industrial workers (-4.3pp, PCS 67). The expansion of the techie occupations is similar in permanent and other firms.

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 mechanically increases inequality, and here we calculate that this is a strong force towards higher inequality in France. While wage

[27] Table 4 omits occupations that amounted to less than 3 percent of sectoral hours in 2002

inequality in our sample is relatively stable, this is the result of opposing forces. While changes in occupational employment shares increase inequality, changes in wages across occupations tend to compress the wage distribution. In other words, if it wasn't for job polarization, France would have experienced a significant compression in the wage distribution.

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

$$\sqrt{\sum_o S_{ot}\left(\frac{w_{ot}}{\overline{w}_t}-1\right)^2} \tag{3}$$

where S_{ot} is the hours share of occupation o, w_{ot} is the average wage of occupation o, and $\overline{w}_t$ is the overall average wage.[28] Occupational inequality as measured by (3) rose a modest 6 percent from 0.485 in 1994 to 0.514 in 2007.

Changes in (3) embody two 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 153% 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 124% of the change. The difference between these two calculation arises from the interaction of changes in relative wages and in occupational employment shares. 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), as discussed above in Section 1.1.

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

[28] 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)). We splice the $w_{ot}/\overline{w}_t$ series between 2001 and 2002, as described in the appendix.

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,

$$X_{ot} = \sum_f x_{ft} s_{fot}, \tag{4}$$

where s_{fot} is the share of occupation o hours in firm f hours. 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.[29] 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 that firms that trade tend to both import and export; e.g., see Bernard, Jensen, Redding, and Schott (2007). 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.

In 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 in 1994.

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.

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

3.4 Techie exposure of occupations

Our working hypothesis is that techies are a key channel that translate falling ICT prices into changes in the firm level occupation mix. An implication is that firms with more techies may 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 short 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 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 paid by occupation o and h_{ft} is total hours in firm f. 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 other occupations o. The diagonal elements are 1 by definition, while the off-diagonal elements answer the question: what share of hours in occupation o' (rows) are worked in firms that also employ occupation o (columns)?

The occupational exposure measures do not change much over time, so we report results for a single year, 2002, in Table 5. 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, Table 5 shows that 55 percent of hours paid 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 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 5 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. The model also shows how a drop in the price of ICT can lead to greater employment growth in ICT-intensive firms. 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 $0 < \sigma < 1$. A key parameter is θ, which indexes the intensity 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' labor hours 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 r 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

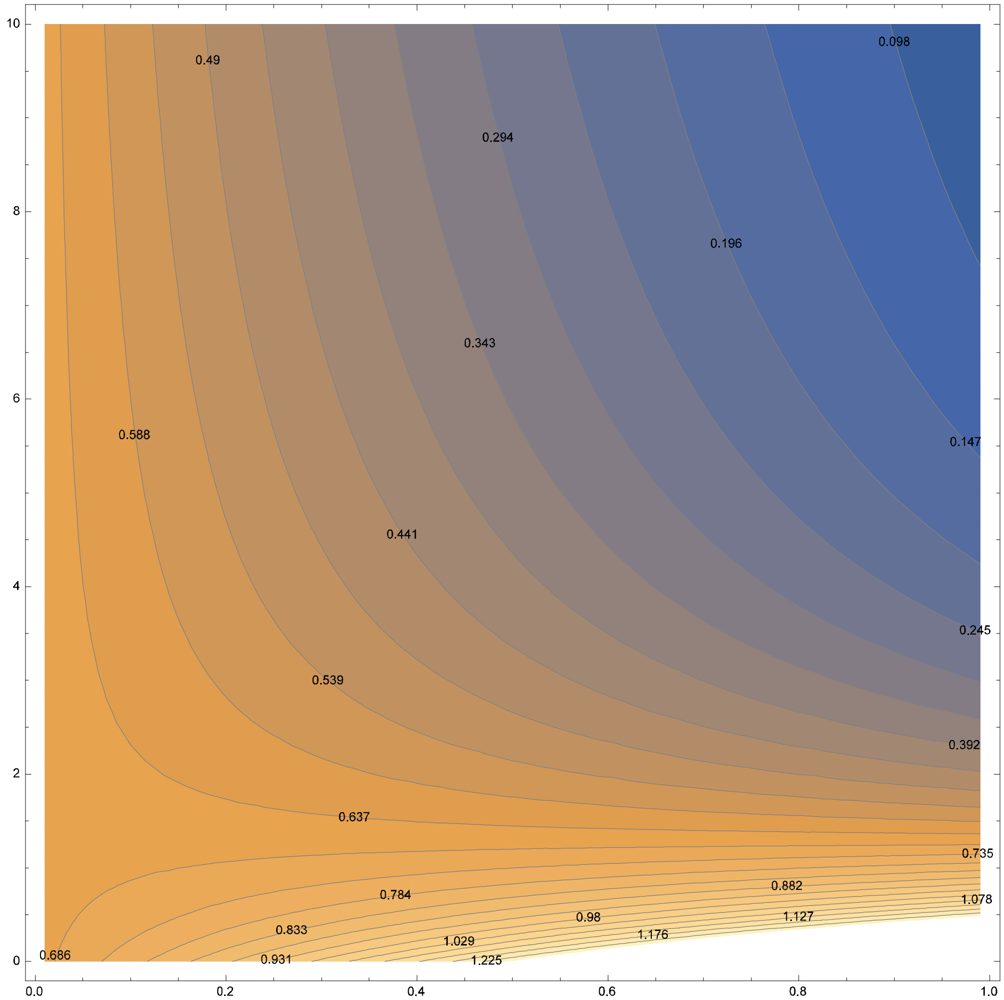


Figure 1: H/M as a function of r (vertical axis) and θ (horizontal axis)

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 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 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 5 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.

4.5 Imports and exports

The model above is silent on globalization as an influence on the level and composition of employment. Rather than incorprate imports and exports formally into the model, we discuss this much-studied issue informally here.

Feenstra and Hanson (1996) seem to have been the first to show how purchases of imported intermediates (offshoring) can affect the skill composition of employment. More recently, Acemoglu and Autor (2011) showed how offshoring can contribute to firm-level polarization. These and related analyses make the point that offshoring has competing effects on total firm-level employment: a direct substitution effect of imported intermediates for workers within the firm, and a cost-reducing effect that can raise demand for workers whose jobs are not offshored.[30] We estimate

[30] Grossman and Rossi-Hansberg (2008) show how this second effect may or may not dominate in general equilibrium.

these polarization and net employment effects in our econometric analysis below.

A large empirical literature—reviewed by Bernard, Jensen, Redding, and Schott (2007)—finds that exporting is associated with higher skill intensity in cross-sections of firms. We know of no theoretical or empirical analysis of the link between exporting and firm-level employment, perhaps because the first-order effect is too obvious: firms that also sell abroad will tend to have greater labor demand than those who sell only at home. In our econometric analysis below we look for such firm-level employment effects both within and between French firms.

5 Econometric analysis of between-firm differences in employment growth

In this section we ask: what accounts for differences across firms in employment growth? The discussion in the previous section suggests that both globalization and technological change are important causal factors, and the purpose of our econometric analysis is to quantify their importance.

5.1 Estimating equations

Optimal firm-level employment depends on both demand and cost conditions. We specify optimal employment in logs for firm f in year t as

$$\ln h_{ft} = \beta_f + D_f \cdot t + \sum_k \beta_k x_{kft} + \varepsilon_{ft} \ . \tag{5}$$

The firm intercept and trend are given by $\beta_f + D_f \cdot t$, while the effect of time-varying firm-specific characteristics is given by $\sum_k \beta_k x_{kft}$. 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, intermediate inputs, and demand shocks. First differencing (5) from $t-1$ to t gives

$$\Delta \ln h_{ft} = D_f + \sum_k \beta_k \Delta x_{kft} + \Delta\varepsilon_{ft} = D_f + u_{ft} \ .$$

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

We model the firm-specific time trend D_f as a function of the *level* of the techie share and trade in time $t-1$. Firms that do not trade at all, and/or 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 non-linearly. To control for the well-established fact that firm growth rates decline with size, we also include h_{ft-1} as a regressor. Finally, we allow D_f to depend on an industry i fixed effect β_i.[31] Let $techies_{t-1}$ be the share of techies in period $t-1$ hours 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). The equation to be estimated is then

$$\begin{aligned}\Delta \ln h_{ft} = \beta_i &+ \beta_1 techies_{ft-1} + \beta_2 techpos_{ft-1} \\ &+ \beta_3 exports_{ft-1} + \beta_4 exppos_{ft-1} \\ &+ \beta_5 imports_{ft-1} + \beta_6 imppos_{ft-1} + \beta_7 h_{ft-1} + u_{ft} \ ,\end{aligned}$$

or, more compactly,

$$\Delta \ln h_{ft} = \beta_i + \beta \mathbf{X}_{ft-1} + u_{ft} \ . \tag{6}$$

Here $\beta_i + \beta \mathbf{X}_{ft-1}$ summarizes the D_f function. The rationale for this specification is that there are industry and/or economy-wide trends in ICT prices and globalization that will affect firms' employment growth differentially through firms' initial levels of techies and trade. For example, a firm with a large techie share will be more responsive to 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 (6) 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, the six parameters of interest $\{\beta_1, ..., \beta_6\}$ are identified by variation across firms within industries in the levels of techies, trade, and employment. Industry-specific factors that may affect growth in firm-level labor demand are controlled for by the industry fixed effects β_i.

The specification in (6) 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 (and vice versa). To allow for this possibility, we also estimate a specification

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

where the effects of techies are interacted with the trade variables,

$$\begin{aligned}\Delta \ln h_{ft} = {} & \beta_i + \beta_1 techies_{ft-1} + \beta_2 techpos_{ft-1} \\ & + \beta_3 exports_{ft-1} + \beta_4 exppos_{ft-1} + \beta_5 imports_{ft-1} + \beta_6 imppos_{ft-1} \\ & + \left(\beta_7 exports_{ft-1} + \beta_8 exppos_{ft-1} + \beta_9 imports_{ft-1} + \beta_{10} imppos_{ft-1}\right) \times techies_{ft-1} \\ & + \left(\beta_{11} exports_{ft-1} + \beta_{12} exppos_{ft-1} + \beta_{13} imports_{ft-1} + \beta_{14} imppos_{ft-1}\right) \times techpos_{ft-1} \\ & + \beta_{15} h_{ft-1} + u_{ft} \ .\end{aligned} \tag{7}$$

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 also report estimates that break down imports by intermediate/final and by source country.

When we estimate (6) and (7) we use growth rates instead of log differences on the left hand side. This has virtually no effect on the results, but it has the advantage of making statements about aggregate employment growth more straightforward. In unreported results, we estimated other non-linear specifications for the D_f function, for example by using indicators for terciles or quartiles of $exports_{ft-1}$ and $imports_{ft-1}$ instead of their values. These deliver very similar magnitudes of the economic effect on firm employment growth. In other words, the main source of non-linearity is the extensive zero/positive margin; once we control for this, further non-linearity is much less important.

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 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 equations (6) and (7) by least squares is unlikely to be consistent for two reasons: endogeneity of the included right hand side variables, and correlation of the included right hand side variables with relevant omitted variables. Here we describe our instrumental variables strategy that delivers a consistent estimator of (6) and (7) in the face of these 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 a change in data processing of the DADS. Consequently, we estimate equations (6) and (7) on the 5 year period 2002 to 2007. The left hand side variable is the growth rate of firm hours between 2002 and 2007, and the initial levels of techies, trade and employment on the right hand side are measured in 2002. Because our data goes back to 1994, we use lagged levels of techies, trade and employment from 1994 to 1998 as instruments for the levels in 2002 (our choice of which years to use as instruments is discussed below). We estimate (6) and (7) separately for manufacturing and nonmanufacturing firms.

Our estimation sample consists of a balanced panel of the 310,713 French private sector firms that have positive hours 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. These 310,713 firms, 85% of whose hours are in nonmanufacturing, account for about half of private sector hours 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. In particular, the trends are virtually the same. 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 two requirements: they must be strong (correlated with the included endogenous variables) and exogenous (uncorrelated with the composite error term u_{ft}). We address these requirements here, but in summary: our instruments are undoubtedly strong, but there are some concerns about exogeneity.

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, also known as C tests.[32] 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 Sargan test statistic is distributed as a χ^2_m, where m is the number of added instruments, which is 7 in our case. The null hypothesis is that the additional instruments are valid, conditional on the previous ones being valid. Failure to reject the null at each increment is taken as evidence for the validity of the added instruments. The results indicate that in nonmanufacturing no more than six lags, including 1994–1999, should be used; in manufacturing the procedure indicates no more than four lags, including 1994–1997, should be used.[33]

Importantly, the lag for which the C stat exeeds conventional critical values is also the lag that is the first to have a Hansen J statistic that exeeds conventional critical values. This is not generally true, but in our case it is. This implies that the overidentification test is not rejected at standard levels of significance for six lags in nonmanufacturing and for four lags in manufacturing. In manufacturing, using five lags from 1994 to 1998 gives a p-value for the J test of 0.03.[34] This is particularly reassuring, because it implies that as a set, lags 1994–1998 can be considered exogenous *a priori*. We chose five lags in both sectors for symmetry.[35]

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.[36] Our benchmark

[32] Convenient references for the "difference-in-Sargan" test include Hayashi (2000), pages 218–221 and 232–234, and Ruud (2000), Chapter 22.

[33] These results are available upon request.

[34] Adding 1999 and 2000 lags increases the p-value somewhat to 0.06.

[35] These results are available upon request.

[36] Of the two minimum MSE crieria proposed by Donald and Newey (2001), we use the Mallows criteria, which proves to be more robust in practice. We consider the simple average of the MSE criterion across the six elements of interest in β.

uses only the 1994 lags of **X**. When we add lags of **X** sequentially and compare the MSE to that of using only 1994, we find that the minimum MSE is attained with six lags in nonmanufacturing and seven lags in manufacturing, which includes 1999 or 2000, respectively.

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 in both the manufacturing and nonmanufacturing sectors.

Are the instruments strong? 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 seven 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 Shea partial R^2s for equation (6) are reported in Table 6, and the results leave no question that the first stage is strong.

Are the instruments excludable? An implication of exogeneity is that the instruments must be excludeable, i.e. not relevant except through their influence on the endogenous regressors. We conduct a specification test that addresses this implication. Our procedure is to add the 1998 lag of techies, trade, and employment to (6), 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 cannot be rejected, which leads us to proceed in assuming that the exclusion restrictions for lags from 1994 to 1998 are valid.

Are the instruments exogenous? For the instruments to be exogenous, they must be uncorrelated with the composite error term u_{it} in (6). Recall that u_{it} includes both changes in firm characteristics x_{kft} and changes in the error term ε_{ft} in (5). Thus our identifying assumption is that five year *changes* in the x_{kft}'s and the error term ε_{ft} 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}, 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 regressions' R^2's 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_{ft} in (5). It is likely that the errors are contemporaneously correlated with the x_{kft}'s, so serial correlation in ε_{ft} implies possible correlation between ε_{ft} and the lagged x_{kft}'s that we use as instruments. However, since it is $\Delta\varepsilon_{ft}$ rather than ε_{ft} that enters our estimating equation (6), what matters for the exogeneity of our instruments is possible correlation between $\Delta\varepsilon_{ft}$ and the lagged x_{kft}'s. In the appendix we show that although serial correlation in ε_{ft} does give rise to bias, this bias is likely to be small.

We have just argued that 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 (6), i.e. misspecification of D_f. 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 we can not test this or rule it out *a priori*.

Table 7 reports p-values for two standard diagnostic tests for 2SLS estimation of equation (6). The rows labeled "Endogeneity, $\chi^2(7)$" test the null hypothesis that OLS is a consistent estimator using a Hausman test, while the rows labeled "Overid, $\chi^2(28)$" test the null hypothesis that the instruments are valid using Hansen's J test.[37] We reject the consistency of OLS at any conventional level of statistical significance. As mentioned above, in nonmanufacturing the Hansen J test is not rejected, while in manufacturing it is, but only once we add the lag 1998 and at the 3% level of significance.

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.

5.2.2 Weighting

The unit of observation in our data is a firm, but our research question concerns aggregate employment. Since the distribution of employment across firms is highly skewed, unweighted regression analysis of (6) 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 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).

5.2.3 Summary of estimation strategy

Here we summarize our estimation strategy for equations (6) and (7). We estimate two regressions, one for nonmanufacturing firms and the other for manufacturing firms. The dependent variable is growth in hours in 2002–2007. The explanatory variables are levels of techies (share of hours), trade (imports and exports, scaled by total firm wage bill), and log hours in 2002. The estimator is weighted two stage least squares, where the instruments are lagged techies, trade, and log hours in 1994–1998. We weight observations by firm hours in 2002. Finally, we compute heteroskedasticity robust covariance matrices.

5.3 Estimation results

The estimated parameters of equations (6) and (7) do not directly address our research questions.[38] Here we focus on two questions:

[37] There are seven degrees of freedom for the Hausman test because there are seven endogenous variables in (6). With five lags of the seven dependent variables, we have 35 instruments, which is why there are 28 degrees of freedom for the J test.

[38] The estimate parameters are reported in the Appendix.

1. What is the effect of an increase from zero to the median of the explanatory variable on the growth in hours? 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 growth in hours? 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 growth in hours.[39] Computing these effects involves calculating the estimated conditional mean at two different points, and then looking at the difference. For equation (6), the formulas for the extensive and intensive margin effects of techies are, respectively,

$$extensive\_techies = \frac{\widehat{\beta}_2 + \widehat{\beta}_1 \times p50\,(techies)}{p75\,(\Delta h_{ft}) - p25\,(\Delta h_{ft})} \tag{8}$$

$$intensive\_techies = \frac{\widehat{\beta}_1 \times [p75\,(techies) - p25\,(techies)]}{p75\,(\Delta h_{ft}) - p25\,(\Delta h_{ft})} \tag{9}$$

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. To understand the scale of these unit-free measures, 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 expected employment growth by 60% of its 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 employment growth equal to 40% of its IQR. In short, the effects we report are similar to elasticities.

The interaction effects estimated in equation (7) 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, 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 (8) and (9), 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. Briefly, techie interaction effects are evaluated at the median value of *exports* and *imports* over their strictly positive range. This means that the effect of *techies* among trading firms is evaluated for a firm with the median level of trade. Similarly, *exports* and *imports* interaction effects are evaluated at the median value of *techies* over it strictly positive range. This means that the effect of trade among techie-intensive firms is evaluated for a firm with the median level of

[39] When we compute the intensive and extensive margin effects we use the percentiles of the distribution of strictly positive values for the explanatory variables.

techies. Tables 8 and 9 report the size of relevant subsamples of firms by techie and trade status.[40]

5.3.1 Techies cause faster employment growth, especially in manufacturing

The effect of techies are reported in Panel A of Table 10, 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). Statistically significantly effects are shaded, and standard errors are reported in italics.[41]

- The first number in Table 10, 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 smaller 0.15 intensive margin effect for these firms (column 4). For nonmanufacturing firms that trade (column 5) the extensive margin effect is not significant, and there is a 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 (see Table 8). But variation in techie intensity within manufacturing firms that trade has an intensive margin effect of 0.26.

Overall, Panel A of Table 10 shows that firms that employed more techies in 2002—both at the extensive and the intesive margins—saw much faster employment growth from 2002 to 2007. 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.

5.3.2 Trade affects employment growth

The overall effects of importing and exporting on employment growth are reported in Panel B of Table 10, first for all firms (columns 1, 2, 5 and 6) and then for firms divided into those who do and

[40] 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 available upon request.

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

do not employ techies (columns 3, 4, 7, and 8). All but one of the estimated effects are statistically 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 (6) 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 11. The first two columns repeat the "overall" estimates from Panel B of Table 10. 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 low-skilled labor, which is also what we find in Table 17 below. 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). The effects of importing in nonmanufacturing are always virtually nil.

- 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, except in nonmanufacturing in column 3, but this is not stable across specifications.

Overall, our results in Tables 17 and 11 support a conclusion that offshoring reduces firm employment growth, and leads to skill upgrading within blue collar workers. In addition, it is striking how stable the techie effects are, especially in manufacturing, across all import specification.

6 Econometric analysis of within-firm changes in occupational structure

In this section we ask: what explains changes in the occupational structure within French firms, and how did this contribute to job polarization? 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 in one of twelve major 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 total firm hours).

6.1 Estimating equations and estimation methodology

Our estimation approach here is very similar to the approach in section 5, so we move quickly. The firm-occupation outcome measure of interest is the ex-techie share of hours of the twelve large non-techie occupations listed in Table 2. For each occupation o, our estimating equation is

$$\Delta s_{fot} = \beta_i^o + \beta^o \mathbf{X}_{ft-1} + u_{ft}^o \ . \tag{10}$$

where $\mathbf{X}$ includes the same regressors as in equations (6) and (7) with the exception of log total hours.[42] The estimator is again weighted 2SLS, where the weights are 2002 hours. The issues of instrument strength and validity are the same as before. The same instrument selection procedure used above still leads us to use lags from 1994–1998 as instruments. Table 13 reports p-values for the Hausman endogeneity tests and Hansen's J tests of the overidentifying restrictions. Table 12 shows that the first stage is strong. We estimate (10) for each occupation o that comprised at least three percent of hours in 2002, separately for manufacturing and nonmanufacturing.

One additional econometric issue is censoring. Firms choose their mix of occupations optimally, and corner solutions are common: few if any firms employ workers in all occupations in every

[42] Overall, the estimates of regressions when we include log total hours as a regressor (and instrument for it accordingly) tell a similar story as the results reported in the paper. This is because in almost all specifications firm size has no effect on the outcome variable. These results are available upon request.

year, and the (weighted) median number of occupations per firm-year is 10.[43] This means that the sample size when estimating (10) varies by PCS code.[44] 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.

6.2 Estimation results

As in Section 5, we report scaled effects rather than regression coefficients[45]. Since the sample changes for each occupation, percentiles that are needed for deriving these scaled effects are computed separately for each occupation in the corresponding sample. Tables 14 through 17 report our results.[46] Rows are occupation-specific regression results. The *Overall* effects in columns (1) and (2) of Tables 14 through 17 are functions of the data and the estimated parameters of our baseline specification, equation (10). The remaining columns are functions of the data and the estimated parameters of the interaction specification, which is similar to equation (7). Statistically significantly effects are shaded, and standard errors are reported in italics.[47]

6.2.1 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 14 show that techies have a large positive effect on within-firm skill upgrading:

- Firms with more techies increase the share of top managers (PCS 37), and the effect is large and statistically significantly. The extensive margin effect, which compares a firm with no techies to one with a median techie share, is that the latter differentially increases the managerial share of hours 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 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 increase their shares (PCS 46, effect is +0.048)

[43] 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.

[44] 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.

[45] Regression coefficients are reported in the appendix.

[46] For each sector, we include estimates only for occupations that amounted to at least 3 percent of hours in 2002.

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

while low-paid office and retail occupations shrink (the effect for Office Workers PCS 54 is -0.055, and for Retail Workers PCS 55 it is -0.15).

- The share of 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.[48]

The final 4 columns of Table 14 shows how the effects of techies varies with firm's trading status:

- For firms that do not trade (58 percent of hours in nonmanufacturing), the extensive margin effect of techies on top manager growth (PCS 37) is half of the IQR for this occupation's share growth for these firms. 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 workers (PCS 62, +1.4) and slower growth for low-skill manual laborers (PCS 68, -0.7).
- For firms that both import and export (26 percent of hours), the extensive margin effects of techies in column 5 are largely unidentified, which is a consequence of the fact that over 90 percent of hours among this group of firms are in firms with techies (see Table 8). The intensive margin effects in column 6 generally line up with the overall intensive margin effects reported in column 2.

6.2.2 Techies cause within-firm skill polarization in manufacturing

Table 15 shows that rather than causing skill upgrading as they do in nonmanufacturing, techies in manufacturing cause skill *polarization* within manufacturing firms. 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 in manufacturing) polarization occurs along the extensive margin, with middle managers growing faster (PCS 46, +0.6) and both clerical office workers (PCS 54, -0.9) and similarly paid middle-wage skilled manual workers (PCS 63, -2.9) reducing their shares within firms.

[48] 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 industrial 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.

6.2.3 Trade affects within-firm skill mix, mostly in manufacturing

Tables 16 and 17 show that trade also affects the within-firm occupational mix, but mainly in manufacturing. Overall, trade has small and mainly statistically insignificant effects on the occupational mix within nonmanufacturing firms. However,

- Importing causes firms to increase their share of drivers and the effect is large (columns 1 and 3 of Table 16). This is true both overall (+0.9) and for firms with techies (+1.24), and is consistent with nonmanufacturing firms that import and have distribution networks.

- Compared to firms that do not export, nonmanufacturing exporters have sharply falling shares of office workers (PCS 54, -0.6), and rising shares of low skill manual workers (PCS 68, +2.4); comparing column 5 to 7 in Table 16, these effects are even larger among firms that have techies (-0.8 and +3.4, respectively).

Given that nonmanufacturing firms do not engage in much direct international trade, the paucity of strong results just described is not surprising. In Table 17 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, +0.4). The effect among firms with techies is similar in size to the overall effect, though imprecisely estimated. 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 and +6.2, respectively), 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 and -3.4 respectively) while the share of unskilled industrial workers grows much faster (PCS 67, +2.1).

The effects are similar among manufacturing importers with techies (columns 3 and 7), which is to be expected, since almost all trading manufacturing firms employ techies (see Table 8). 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.

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.[49]

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 surprising 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.

Overall, our results in Tables 17 and 11 support a conclusion that offshoring reduces firm employment growth, and leads to skill upgrading within blue collar workers.

7 Econometric Results: Goodness of fit

Our final quantitative question is: 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 (10), and then divide this by the actual within component for permanent

[49] 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.

firms from 2002 to 2007,

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

where $\overline{\lambda}_f$ is the average hours share of firm f from 2002 to 2007.[50] *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 (6), and then divide this by the actual between component for permanent firms from 2002 to 2007,

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

where $\widehat{\Delta\lambda}_{ft}$ is approximated by using $\widehat{g}_{ft}$.[51]

Table 13 reports the weighted R^2 and *Explained within* goodness of fit statistics for the estimates of our baseline specification, equation (10). Similarly, Table 7 reports the weighted R^2 and *Explained between* goodness of fit statistics for the estimates of equation (6). 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 7 are even weaker, with 10 of the 24 being negative. 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 13 and 7 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 (10) at conventional significance levels for all the PCS codes in manufacturing, and for nine of twelve in nonmanufacturing. For equation (6) this null is rejected for both nonmanufacturing and manufacturing.

[50] 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.

[51] 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 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 within economic units miss an important margin of adjustment. The importance of changes in the composition of firms for explaining job polarization suggests differential effects of technological change and trade on relative competitiveness across firms.

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 caused slower employment growth in manufacturing, while exporting had 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 and causal econometric analysis, which has made it possible to paint a rich and nuanced portrait of how and why polarization evolved in France between 1994 and 2007.

References

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999): "High wage workers and high wage firms," *Econometrica*, 67(2), 251–333.

Acemoglu, D., and D. Autor (2011): "Skills, tasks and technologies: Implications for employment and earnings," in *Hanbook of Labor Economics*, ed. by O. Ashenfelter, and D. Card, vol. 4b. North Holland.

Amar, M. (2010): "Les très hauts salaires du secteur privé," *insee première*, 1288, 4.

Askenazy, P. (2013): "Working time regulation in France from 1996 to 2012," *Cambridge Journal of Economics*, 37, 323–347.

Autor, D. H., and D. Dorn (2013): "The growth of low-skill service jobs and the polarization of the US labor market," *The American Economic Review*, 103(5), 1553–1597.

Autor, D. H., D. Dorn, and G. H. Hanson (2013): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *The American Economic Review*, 103(6), 2121–2168.

Autor, D. H., L. F. Katz, and M. S. Kearney (2006): "The Polarization of the U.S. Labor Market," *The American Economic Review, AEA Papers and Proceedings*, 96(2), 189–194.

——— (2008): "Trends in U.S. Wage Inequality: Revising the Revisionists," *The Review of Economics and Statistics*, 90(2), 300–323.

Autor, D. H., F. Levy, and R. J. Murnane (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 118(4), 1279–1333.

Beaudry, P., M. Doms, and E. Lewis (2010): "Should the Personal Computer be Considered a Technological Revolution? Evidence from U.S. Metropolitan Areas," *Journal of Political Economy*, 118(5), 988–1036.

Becker, S. O., and M.-A. Muendler (2014): "Trade and Tasks: An Exploration over Three Decades in Germany," NBER Working Paper No. 20739.

Berman, E., J. Bound, and Z. Griliches (1994): "Changes in the Demand for Skilled Labor Within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures," *The Quarterly Journal of Economics*, 109(2), 367–397.

Bernard, A., B. Jensen, S. Redding, and P. Schott (2007): "Firms in International Trade," *Journal of Economic Perspectives*, 21(3), 105–130.

Bernard, A. B., E. J. Blanchard, I. Van Beveren, and H. Y. Vandenbussche (2012): "Carry-along trade," Discussion paper, National Bureau of Economic Research.

Bernard, A. B., and J. B. Jensen (1997): "Exporters, Skill Upgrading, and the Wage Gap," *Journal of International Economics*, 42(1), 3–31.

Biscourp, P., and F. Kramarz (2007): "Employment, skill structure and international trade: Firm-level evidence for France," *Journal of International Economics*, 72(1), 22–51.

Blinder, A. S., and A. B. Krueger (2013): "Alternative Measures of Offshorability: A Survey Approach," *Journal of Labor Economics*, 31(2), S97–S128.

Böckerman, P., S. Laaksonen, and J. Vainiomäki (2013): "Is there job polarization at the firm level?," .

Bound, J., D. A. Jaeger, and R. M. Baker (1995): "Problems with Instrumental Variables Estimation when the Correlation Between the Instruments and the Endogenous Explanatory Variable is Weak," *Journal of the American statistical association*, 90(430), 443–450.

Bozio, A., T. Breda, and M. Guillot (2016): "Taxes and Technological Determinants of Wage Inequalities: France 1976-2010," Working Paper, Paris School of Economics (PSE) and Institut des politiques publiques (IPP).

Card, D., F. Kramarz, and T. Lemieux (1999): "Changes in the Relative Structure of Wages and Employment: A Comparison of the United States, Canada, and France," *Canadian Journal of Economics*, 32, 843–877.

Carluccio, J., D. Fougere, and E. Gautier (2014): "Trade, Wages, and Collective Bargaining: Evidence from France," Banque de France Working Paper No. 498.

Charnoz, P., E. Coudin, and M. Gaini (2013): "Decreasing Wage Inequality in France 1967-2009: The roles of supply, demand and institutions," Working Paper, CREST-INSEE, February 2013.

Cortes, G. M., N. Jaimovich, C. J. Nekarda, and H. E. Siu (2014): "The Micro and Macro of Disappearing Routine Jobs: A Flows Approach," NBER Working Paper No. 20307.

Cortes, G. M., and A. Salvatori (2015): "Task Specialization within Establishments and the Decline of Routine Employment," working paper, University of Manchester.

Cowell, F. A. (2008): *Measuring Inequality*. Oxford University Press.

Donald, S. G., and W. K. Newey (2001): "Choosing the Number of Instruments," *Econometrica*, 69(5), 1161–1191.

Dustmann, C., J. Ludsteck, and U. Schönberg (2007): "Revisiting the German wage structure," *The Quarterly Journal of Economics*, 124(2), 843–881.

Feenstra, R. C., and G. H. Hanson (1996): "Foreign Investment, Outsourcing, and Relative Wages," in *The Political Economy of Trade Policy*, ed. by G. M. Grossman, R. C. Feenstra, and D. R. Irwin, pp. 89–127. MIT Press, Oxford.

——— (1999): "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979-1990," *The Quarterly Journal of Economics*, 114(3), 907–940.

Firpo, S., N. M. Fortin, and T. Lemieux (2011): "Occupational Tasks and Changes in the Wage Structure," Working Paper, University of British Columbia.

Godechot, O. (2012): "Is Finance Responsible for the Rise in Wage Inequality in France?," *Socio-Economic Review*, 10, 447–470.

Goos, M., and A. Manning (2007): "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain," *The Review of Economics and Statistics*, 89(1), 118–133.

Goos, M., A. Manning, and A. Salomons (2009): "Job Polarization in Europe," *The American Economic Review, AEA Papers and Proceedings*, 99(2), 58–63.

——— (2014): "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *The American Economic Review*, 104(8), 2509–2526.

Goux, D., and E. Maurin (2000): "The decline in demand for unskilled labor: an empirical analysis method and its application to France," *Review of Economics and Statistics*, 82(4), 596–607.

Grossman, G. M., and E. Rossi-Hansberg (2008): "Trading Tasks: A Simple Theory of Offshoring," *The American Economic Review*, 98(5), 1978–97.

Harrigan, J., and A. Reshef (forthcoming): "Skill Biased Heterogeneous Firms, Trade Liberalization and the Skill Premium," *Canadian Journal of Economics*.

Hayashi, F. (2000): *Econometrics*. Princeton University Press, Princeton, NJ.

Jaimovich, N., and H. E. Siu (2012): "The Trend is the Cycle: Job Polarization and Jobless Recoveries," NBER Working Paper No. 18334.

Katz, L. F., and K. M. Murphy (1992): "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," *The Quarterly Journal of Economics*, 107(1), 35–78.

Keller, W., and H. Utar (2015): "International Trade and Job Polarization: Evidence at the Worker Level," Preliminary and Incomplete Draft (December).

Kerr, S. P., T. Maczuskij, and M. Maliranta (2015): "Within and Between Firm Trends in Job Polarization: Role of Globalization and Technology," draft (October), Wellesley College.

Kramarz, F. (2008): "Offshoring, Wages, and Employment: Evidence from Data Matching Imports, Firms, and Workers," CREST-INSEE mimeo.

Landais, C. (2008): "Top Incomes in France: booming inequalities?," Paris School of Economics, Mimeo.

Maurin, E., and D. Thesmar (2004): "Changes in the Functional Structure of Firms and the Demand for Skill," *Journal of labor economics*, 22(3), 639–664.

Maurin, E., M. Thoenig, and D. Thesmar (2002): "Globalization and the Demand for Skill: An Export-Based Channel," CEPR Discussion Paper No. 3406.

Michaels, G., A. Natraj, and J. Van Reenen (2014): "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years," *Review of Economics and Statistics*, 96(1), 60–77.

Moreno-Galbis, E., and T. Sopraseuth (2014): "Job polarization in aging economies," *Labour Economics*, 27, 44–55.

Oesch, D. (2013): *Occupational Change in Europe*. Oxford University Press, United Kingdom.

Piketty, T. (2014): *Capital in the Twenty-first Century*. Harvard University Press.

Postel-Vinay, F., and J.-M. Robin (2006): *Microeconometric search-matching models and matched employer-employee data*. Cambridge University Press.

Rodriguez-Clare, A. (2010): "Offshoring in a Ricardian World," *American Economic Journal: Macroeconomics*, 2(2), 227–58.

Ruud, P. A. (2000): *An Introduction to Classical Econometric Theory*. Oxford University Press, Oxford.

Shea, J. (1997): "Instrument Relevance in Multivariate Linear Models: A Simple Measure," *Review of Economics and Statistics*, 79(2), 348–352.

Spitz-Oener, A. (2006): "Technical Change, Job Tasks and Rising Educational Demands: Looking Outside the Wage Structure," *Journal of Labor Economics*, 24(2), 235–270.

Staiger, D., and J. H. Stock (1997): "Instrumental Variables Regression with Weak Instruments," *Econometrica*, 65(3), 557–586.

Stock, J. H., and M. Yogo (2005): "Testing for weak instruments in linear IV regression," in *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, ed. by D. W. Andrews, J. H. Stock, and T. J. Rothenberg. Cambridge University Press.

Thesmar, D., and M. Thoenig (2000): "Creative destruction and firm organization choice," *Quarterly Journal of Economics*, pp. 1201–1237.

Verdugo, G. (2014): "The great compression of the French wage structure, 1969–2008," *Labour Economics*, 28, 131–144.

Verhoogen, E. A. (2008): "Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector," *The Quarterly Journal of Economics*, 123, 489–530.

9 Figures and Tables

Table 1: PCS Occupations

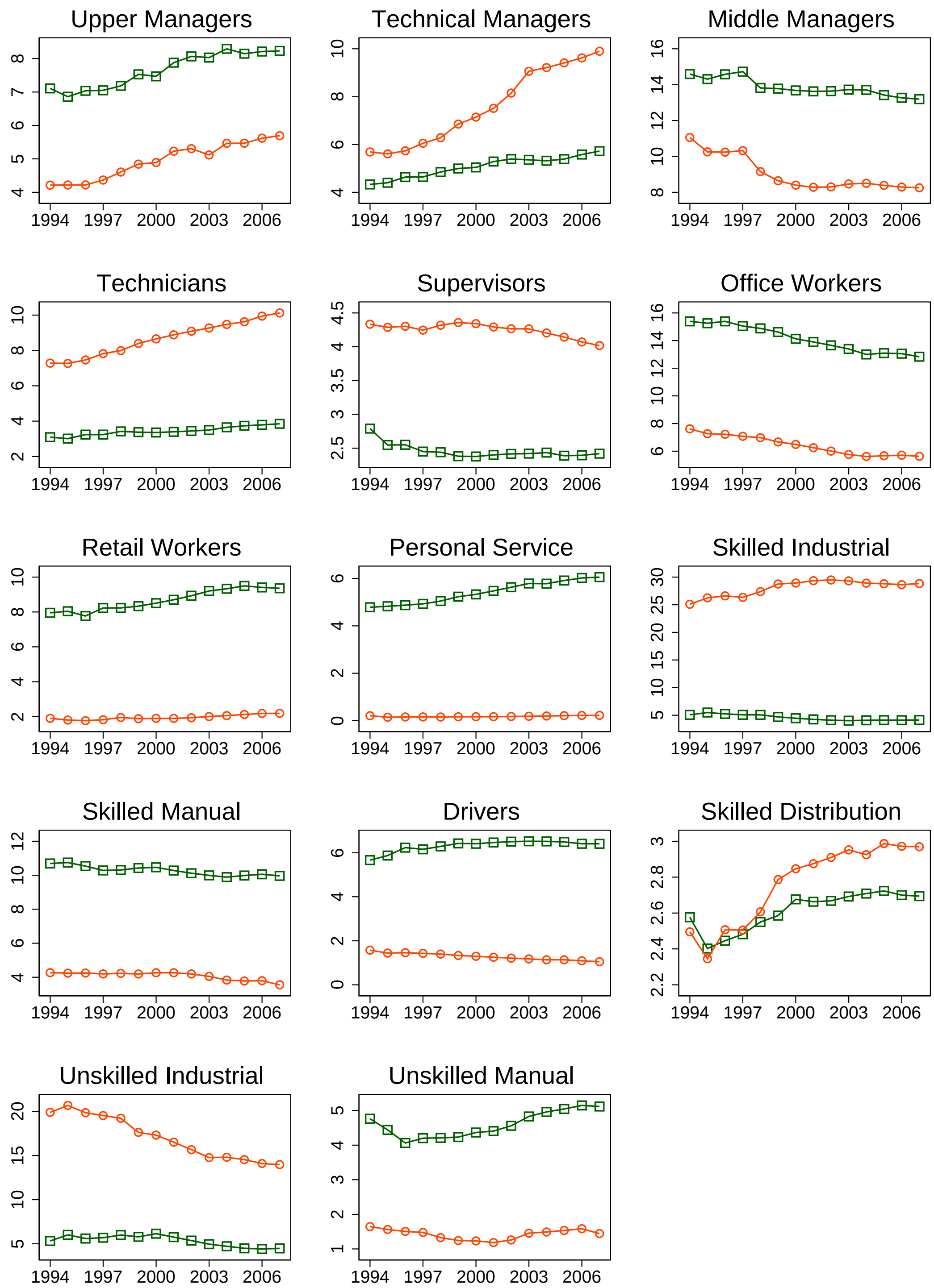
PCS code	description of occupation	rank	share
21	Small business owners and workers	7	0.1
22	Shopkeepers	3	0.2
23	Heads of businesses	1	0.7
34	Scientific and educational professionals	5	0.5
35	Creative professionals	6	0.6
37	**Top managers and professionals**	**2**	**7.3**
38	**Technical managers and 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 paid in 2002. Occupations in bold are account for at least 2.5 percent of hours.

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

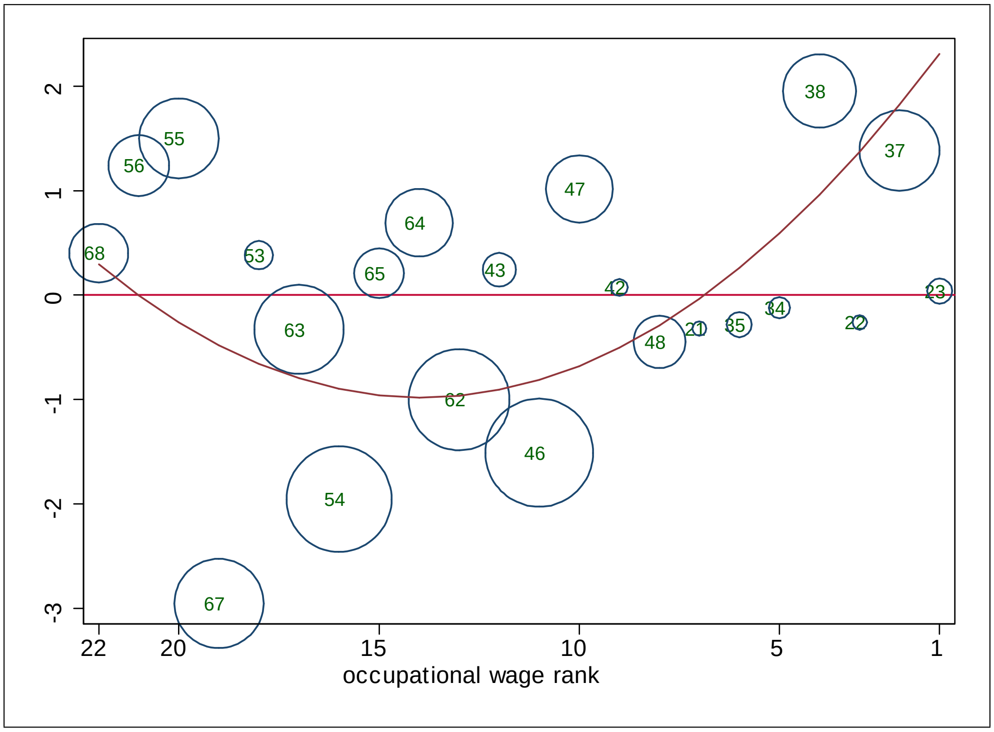
37	**Top managers and professionals**	**56**	**Personal service workers**
	Managers of large businesses		Restaurant servers, food prep workers
	Finance, accounting, sales, and advertising managers		Hotel employees: front desk, cleaning, other
	Other administrative managers		Barbers, hair stylists, and 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 1994-2007



Manufacturing (red circle), Nonmanufacturing (green square)

Figure 3: Change in employment shares 1994–2007, whole economy



Notes to Figures 3, 4, and 5: Vertical axis is change in occupation's share of aggregate hours paid 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 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 employment shares 1994–2007, Nonmanufacturing

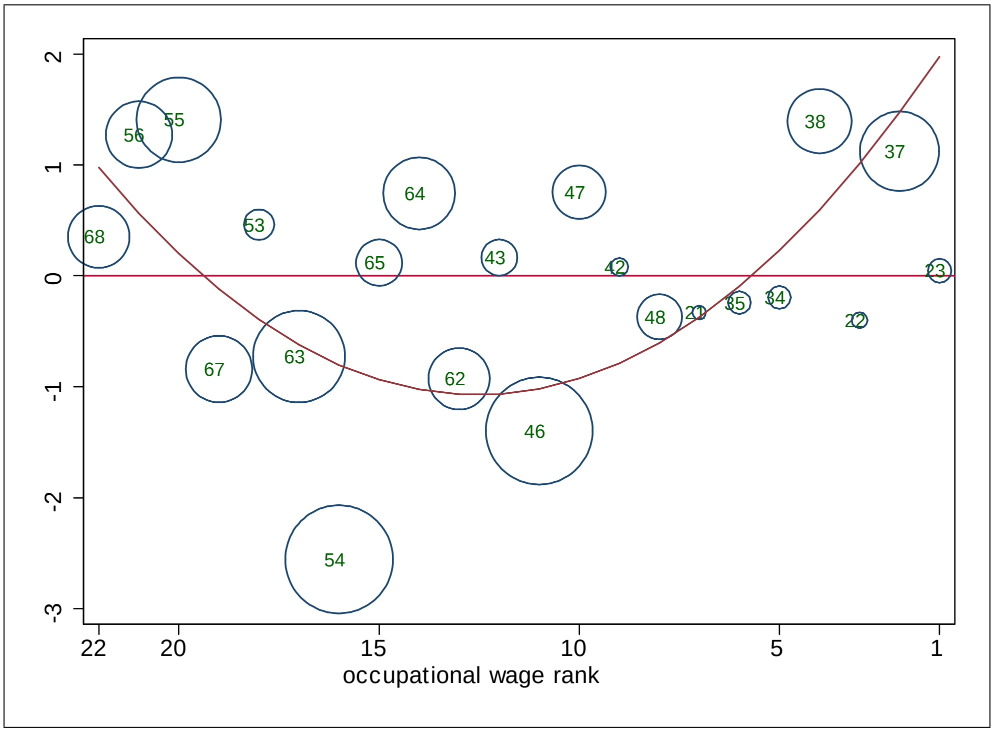


Figure 5: Change in employment shares 1994-2007, Manufacturing

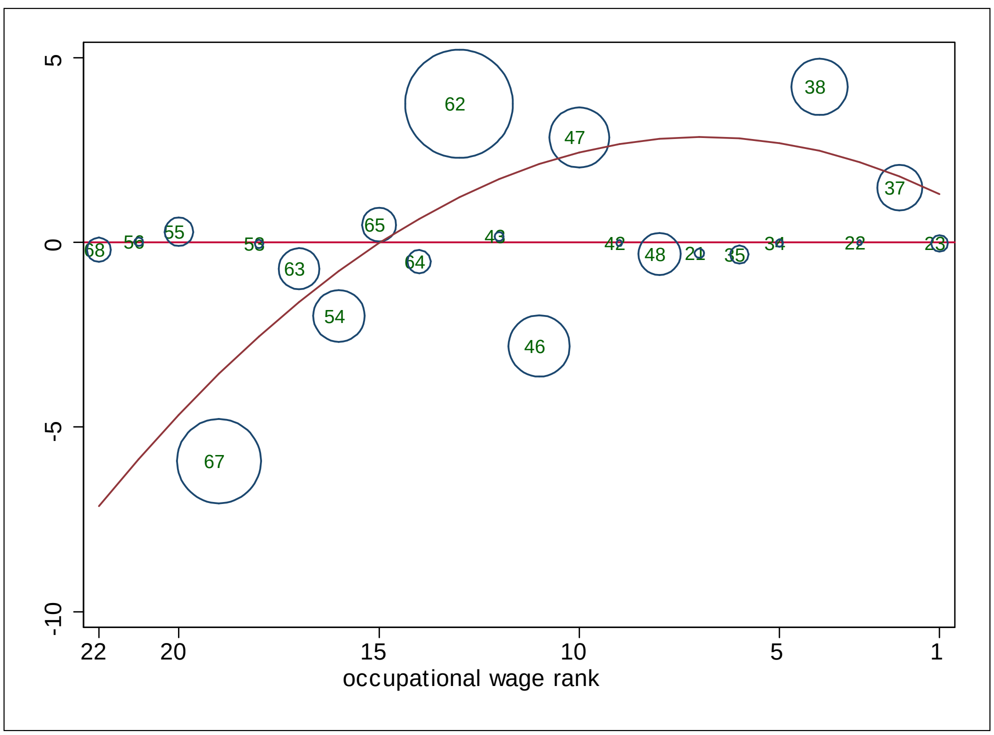
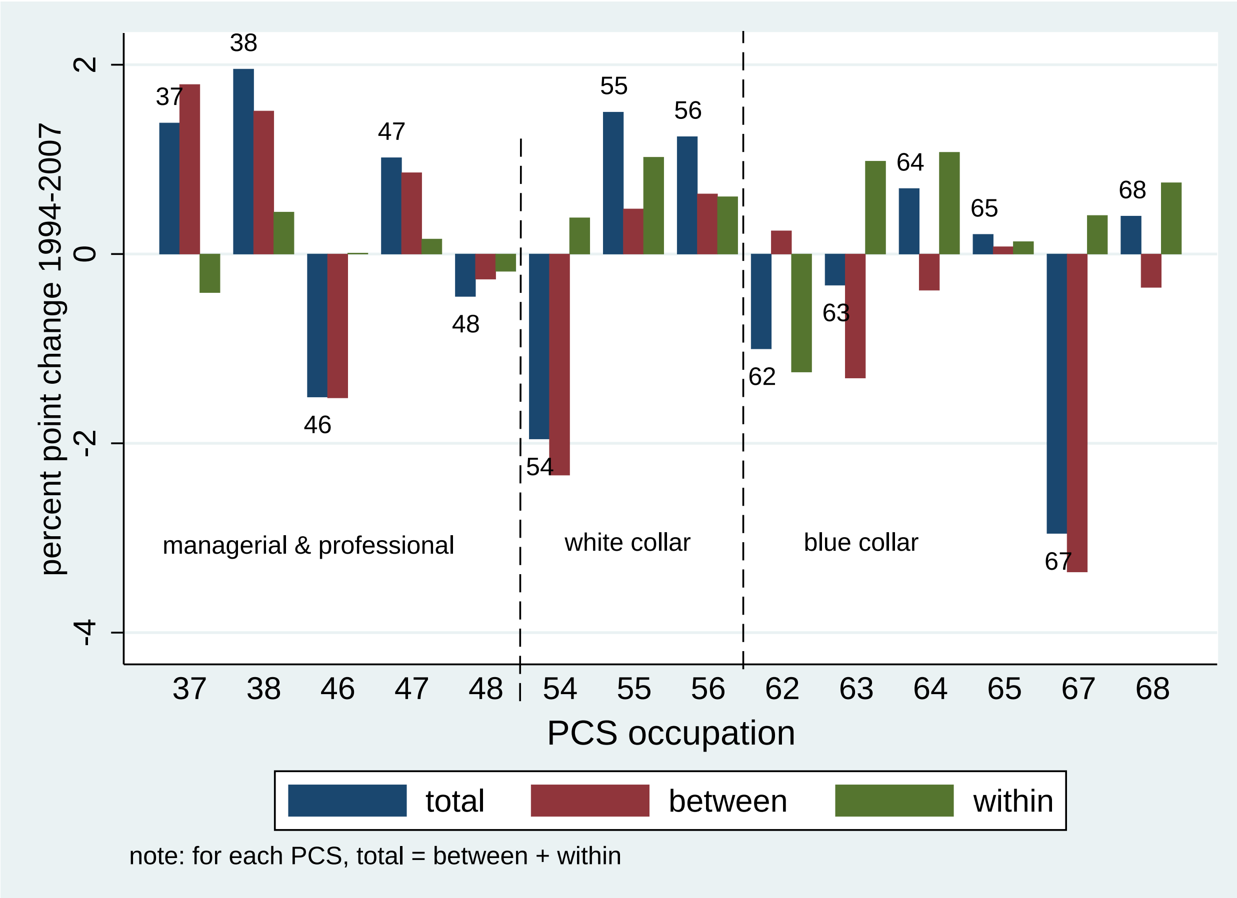


Table 3: Changes in occupational hours share: Between-Within decomposition (1994-2007)

		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 manual laborer	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 manual laborer	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 to Table 3: *Rank* orders PCS codes according to occupational mean wage in 2002. *Share* is time average revised levels of hours shares. 14 largest occupations are boxed.

Figure 6: Within-between decomposition, all firms 1994-2007



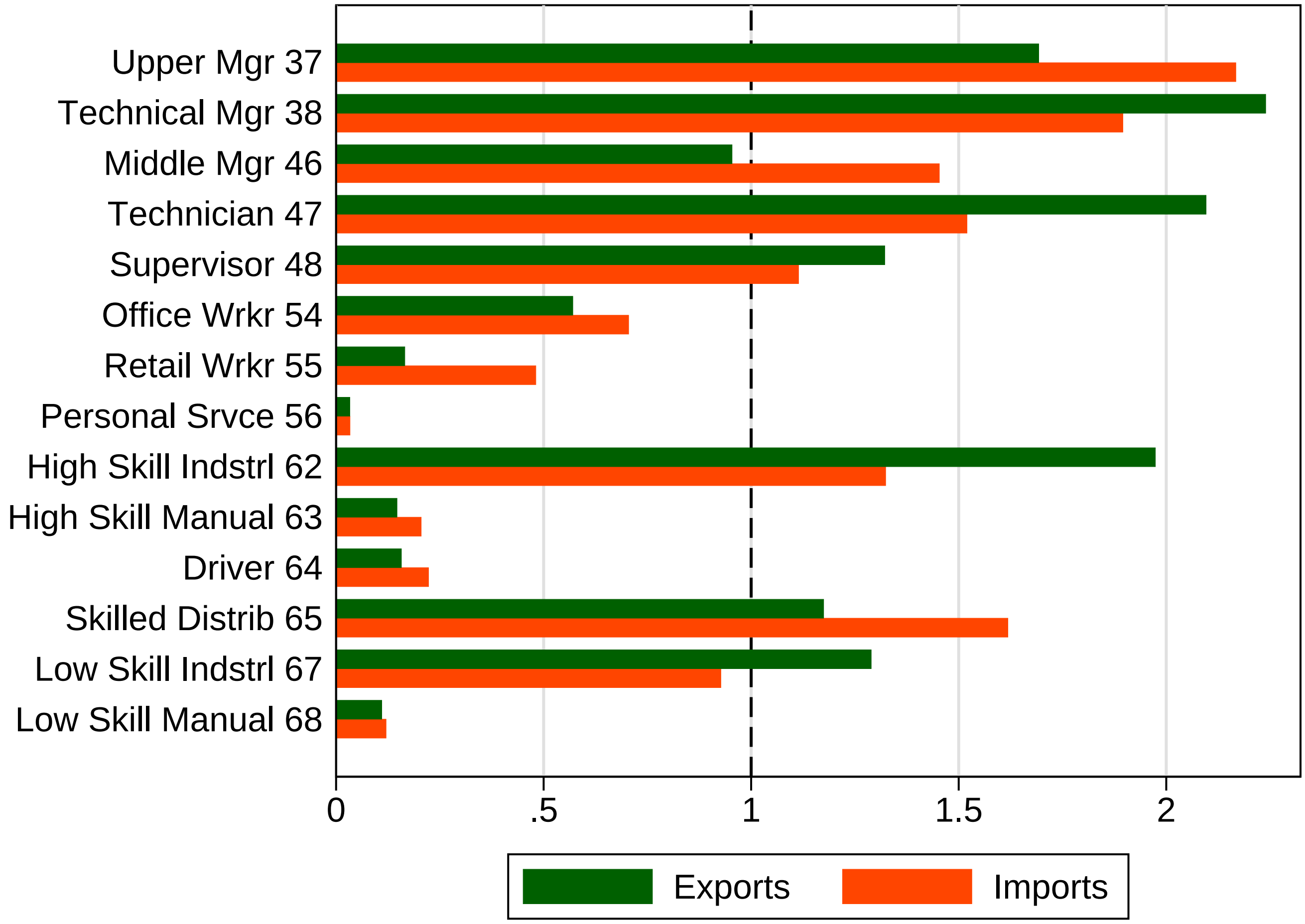
Notes to Table 3 and Figure 6: Changes in share of occupational hours paid from 1994 to 2007 are decomposed into within-firm and between-firm changes using equation (1). For key to occupations, see Tables 1 and 2.

Table 4: Between-Within decomposition 1994-2007, permanent firms and net entry

		All firms		Permanent firms		All other firms	
		2002 share	Change 94-07	Between-p	Within-p	Net entry	Share of total
	PCS2	(1)	(2)	(3)	(4)	(5)	(6)
		Non-manufacturing					
37	Top managers and professionals	8.1	1.12	1.25	-0.25	0.11	0.10
38	Technical managers and engineers	5.4	1.39	0.39	0.20	0.80	0.57
46	Mid-level managers and professionals	13.6	-1.40	0.00	-0.33	-1.07	0.76
47	Technicians	3.4	0.76	0.22	0.22	0.32	0.42
54	Office workers	13.7	-2.56	-1.54	0.04	-1.05	0.41
55	Retail workers	8.9	1.41	0.31	0.43	0.67	0.48
56	Personal service workers	5.6	1.27	0.14	-0.03	1.16	0.91
62	Skill industrial workers	4.1	-0.93	-0.18	0.05	-0.79	0.86
63	Skill manual laborers	10.1	-0.73	-0.13	-0.06	-0.54	0.75
64	Drivers	6.5	0.74	0.20	0.73	-0.18	-0.25
67	Unskill industrial workers	5.4	-0.84	-0.73	0.54	-0.65	0.77
68	Unskill manual laborers	4.6	0.35	-0.04	0.25	0.14	0.40
		Manufacturing					
37	Manager	5.3	1.48	0.84	0.36	0.28	0.19
38	Technical mgr	8.2	4.21	2.60	0.33	1.28	0.30
46	Midddle manager	8.3	-2.80	-1.05	0.48	-2.24	0.80
47	Technician	9.1	2.84	1.70	0.42	0.73	0.26
48	Supervisor	4.3	-0.32	-0.26	0.37	-0.42	1.34
54	Office wrkr	6.0	-1.99	-1.10	0.42	-1.31	0.66
62	Skill industrial wrkr	29.5	3.75	2.10	2.06	-0.42	-0.11
63	Skill manual labor	4.2	-0.72	-0.99	0.77	-0.50	0.70
67	Unskill industrial wrkr	15.7	-5.92	-2.99	1.36	-4.29	0.72

Notes to Table 4: Column (2) = Column (3) + Column (4) + Column (5), Column (6) = Column (5)/Column (2). PCS codes with 2002 hours shares less than 3 percent not reported.

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



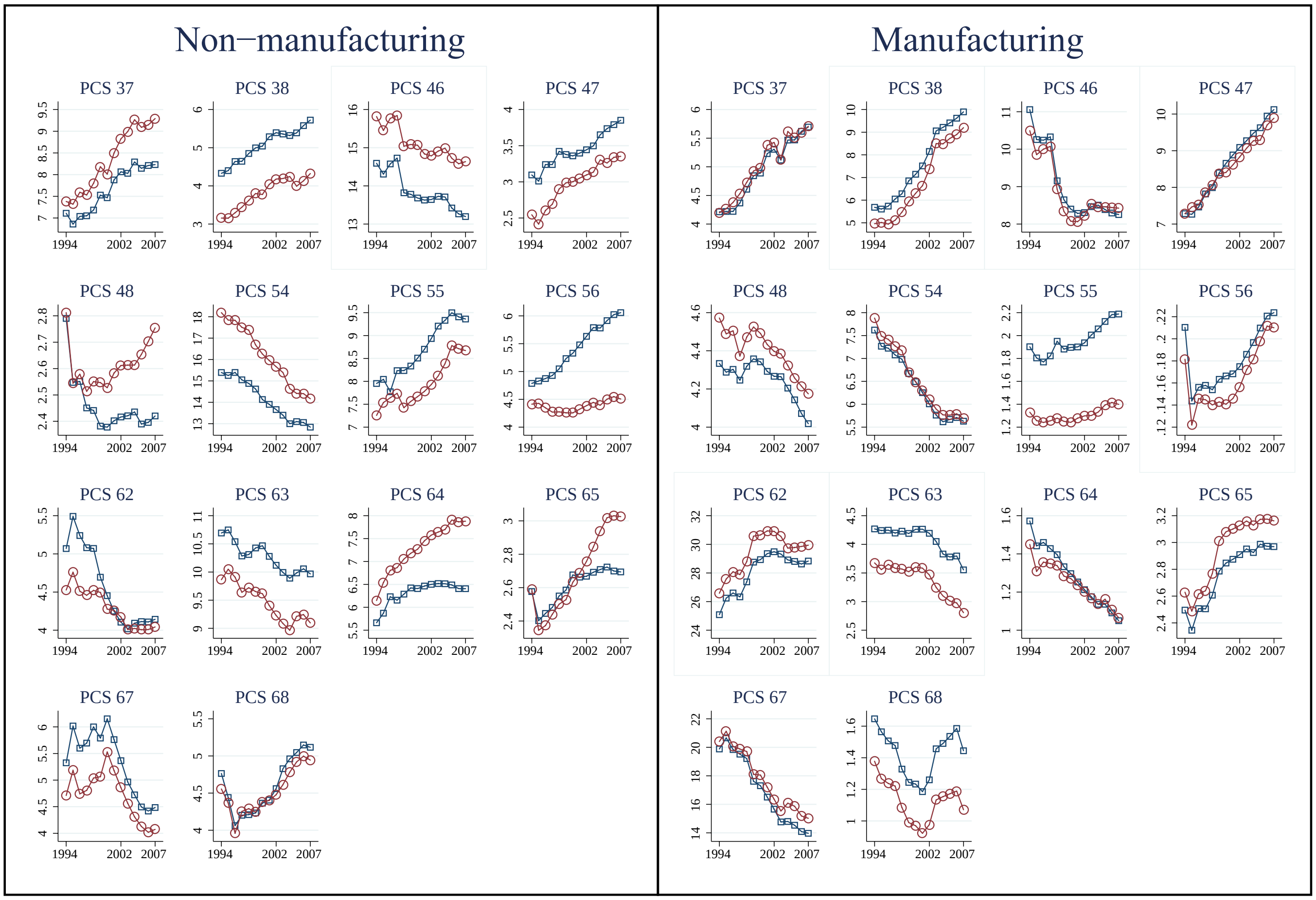
Notes to Figure 7: Occupational trade exposure defined by equation (4). Figure shows average relative exposure from 1994 to 2007.

Table 5: 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 manual laborer	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 manual laborer	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.

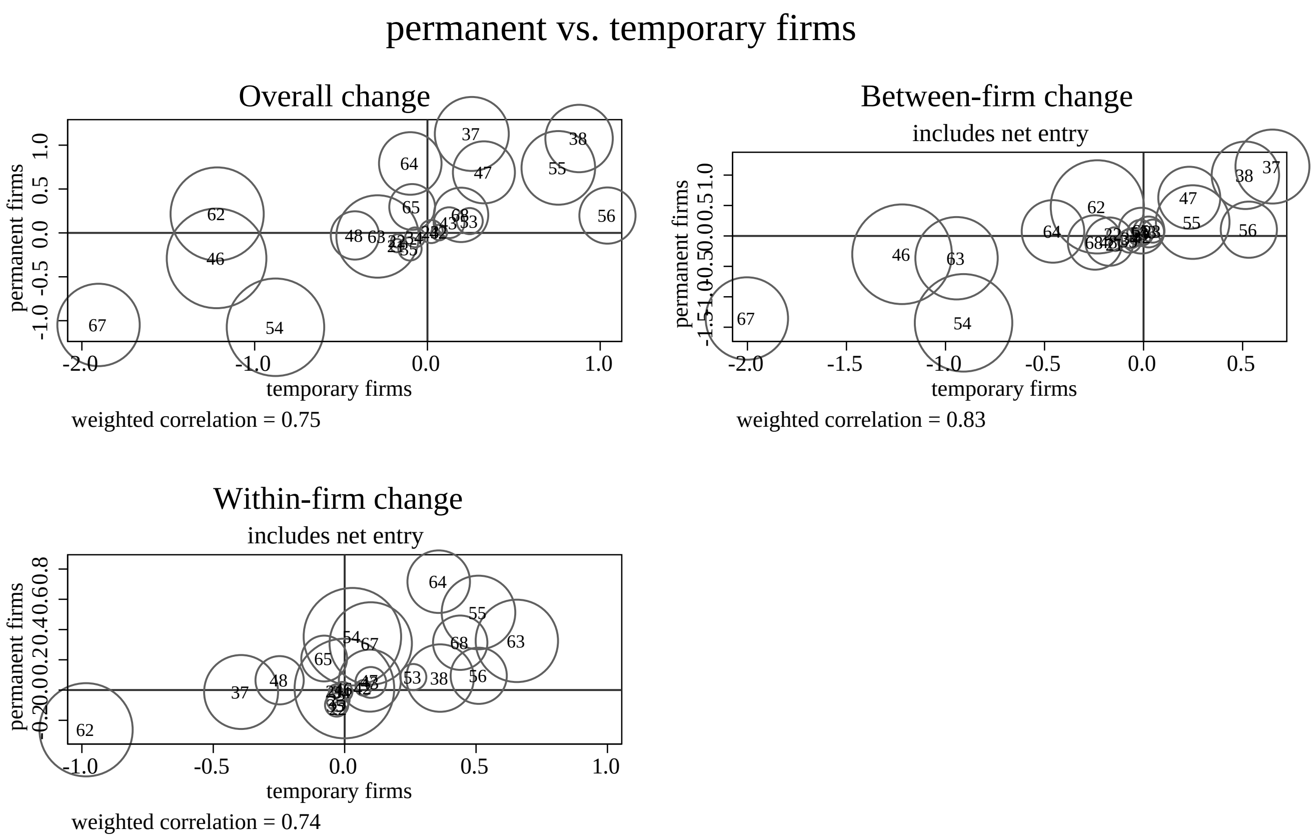
Figure 8: Occupational hours shares for all firms and permanent firms



Blue box: All firms
Red circle: Permanent firms

Notes to Figures 8 and 9:'Permanent" firms are those with positive hours 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 6: 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 6: Reports first stage goodness of fit measure for 2SLS estimation of equation (6). 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 7: 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, $\chi^2(28)$	0.38	0.03

Notes to Table 7: Statistics based on 2SLS estimates of equation (6).

Table 8: Shares of hours

techies?	nonmanufacturing 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

techies?	manufacturing 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 9: 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 8 and 9: These tables report cross tabs of frequencies for the estimation sample.

Table 10: 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. Regression results reported in Appendix Tables 21 and 22

Table 11: Effects of techies, exports and different classes of imports on employment growth rates

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. Regression results reported in Appendix Tables 21 and 22

Table 12: Shea first stage partial R^2

Nonmanufacturing:

PCS	37	46	54	55	56
Techies 2002	0.669	0.657	0.657	0.640	0.744
Techies 2002 >0	0.245	0.262	0.275	0.306	0.305
Imports 2002	0.603	0.600	0.601	0.633	0.694
Imports 2002 >0	0.204	0.210	0.211	0.228	0.171
Exports 2002	0.550	0.560	0.556	0.573	0.587
Exports 2002 >0	0.210	0.214	0.214	0.239	0.197

PCS	62	63	64	67	68
Techies 2002	0.708	0.665	0.681	0.697	0.664
Techies 2002 >0	0.242	0.295	0.280	0.268	0.290
Imports 2002	0.630	0.626	0.642	0.622	0.642
Imports 2002 >0	0.189	0.217	0.211	0.209	0.209
Exports 2002	0.590	0.538	0.566	0.578	0.543
Exports 2002 >0	0.202	0.219	0.207	0.221	0.217

Manufacturing:

PCS	37	46	48	54	62
Techies 2002	0.561	0.550	0.563	0.551	0.542
Techies 2002 >0	0.142	0.167	0.147	0.171	0.168
Imports 2002	0.571	0.571	0.573	0.562	0.564
Imports 2002 >0	0.131	0.136	0.126	0.140	0.138
Exports 2002	0.681	0.679	0.681	0.677	0.674
Exports 2002 >0	0.183	0.183	0.172	0.186	0.185

PCS	63	64	67
Techies 2002	0.556	0.550	0.551
Techies 2002 >0	0.171	0.180	0.169
Imports 2002	0.598	0.581	0.567
Imports 2002 >0	0.113	0.135	0.137
Exports 2002	0.701	0.720	0.675
Exports 2002 >0	0.165	0.204	0.184

Notes to Table 12: Reports first stage goodness of fit measure for 2SLS estimation of equation (10). 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 13: Second stage goodness of fit and test statistics, baseline within regressions

Nonmanufacturing:

PCS	37	46	54	55	56
Goodness of fit					
Weighted R^2	0.052	0.017	0.034	0.017	0.020
Explained within	-2.827	-0.714	2.410	0.346	-0.664
p-values					
Joint significance; $\chi^2(6)$	0.000	0.029	0.000	0.040	0.044
Endogeneity; $\chi^2(6)$	0.000	0.000	0.000	0.000	0.000
Overid; $\chi^2(24)$	0.000	0.000	0.000	0.000	0.000

PCS	62	63	64	67	68
Goodness of fit					
Weighted R^2	0.035	0.003	0.017	0.050	0.033
Explained within	8.162	0.669	-0.136	1.834	0.158
p-values					
Joint significance; $\chi^2(6)$	0.244	0.005	0.111	0.061	0.015
Endogeneity; $\chi^2(6)$	0.000	0.000	0.000	0.000	0.000
Overid; $\chi^2(24)$	0.000	0.000	0.000	0.000	0.000

Manufacturing:

PCS	37	46	48	54	62
Goodness of fit					
Weighted R^2	0.067	0.035	0.015	0.030	0.176
Explained within	-17.185	0.249	0.100	-0.798	-0.096
p-values					
Joint significance; $\chi^2(6)$	0.000	0.000	0.017	0.000	0.000
Endogeneity; $\chi^2(6)$	0.000	0.000	0.000	0.000	0.000
Overid; $\chi^2(24)$	0.000	0.000	0.038	0.000	0.000

PCS	63	64	67
Goodness of fit			
Weighted R^2	0.064	0.013	0.376
Explained within	1.277	-24.195	0.788
p-values			
Joint significance; $\chi^2(6)$	0.000	0.000	0.000
Endogeneity; $\chi^2(6)$	0.000	0.001	0.000
Overid; $\chi^2(24)$	0.000	0.990	0.000

Notes to Table 13: Statistics based on 2SLS estimates of equation (10).

Notes to Tables 14 through 17: The tables on the following four pages report estimated effects derived from 2SLS estimation of equations (10) (columns labeled *overall)* and interaction specifications (other columns). Reported effects are functions of the estimated parameters and moments of the data. Effects highlighted in yellow are statistically significantly different from zero at the 90 percent level or more.

Table 14: 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*
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*
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. Regression results reported in Appendix Tables 23 and 24

Table 15: 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*
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*
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*

Standard errors italicized. Regression results reported in Appendix Tables 25 and 26

Table 16: 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*
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*
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. Regression results reported in Appendix Tables 23 and 24

Table 17: 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*
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*
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*

Standard errors italicized. Regression results reported in Appendix Tables 25 and 26