

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

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## Abstract

Using administrative employee-firm-level data 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 occurred 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.

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

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

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# 1 Introduction

*Job polarization*—growth in the shares of high-wage and low-wage jobs at the expense of middle wage jobs—is one of the most striking phenomena in many advanced economies’ labor markets in the last several decades.<sup>1</sup> 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 illustrate that industry-level analysis can be misleading when studying the mechanisms underlying aggregate adjustment. 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 where they work. Our measure of technology at the firm level is 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.

## 1.1 Techies

A novel contribution of our paper is our focus on the firm-level employment share of techies. We focus on techies because of their central role in planning, installing, and maintaining information and computer technology (ICT), as well as in training and assisting other workers in the use of ICT. These roles make techies the crucial link between economywide technological progress and firm

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<sup>1</sup>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)).

level technology adoption: as noted by Tambe and Hitt (2014), "the technical know-how required to implement new IT innovations is primarily embodied within the IT workforce" in a firm. Brynjolfsson and Hitt (2003) observe that "In recent years, companies have implemented thousands of large and small innovations in software applications, work processes, business organization, supply-chain management, and customer relationship management". Implementation of these innovations was undoubtedly mediated by techies, who are a good measure of the "organizational capital" that Brynjolfsson and Hitt (2003) argue is crucial to ICT adoption. Of course, not all technological change comes through ICT investment, and our measure of techies includes engineers, technology managers, and technicians more broadly. Our paper is the first to measure the number of these workers at the firm level in the entire economy, which allows us to estimate the effect of techies on firm outcomes including job polarization and firm growth.

## 1.2 Preview of findings

We show that, like several other countries, France has experienced job polarization: employment shares of high-wage managers and professionals increased; shares of middle income office workers and industrial workers fell; and 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 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)).<sup>2</sup> 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.<sup>3</sup>

We decompose changes in employment shares into two components: within-firm changes and composition changes due to changes in firm sizes (including entry and exit). We find that these

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<sup>2</sup>See Goos, Manning, and Salomons (2014) for a comparison across European countries, including France.

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

two dimensions explain varying shares of changes in employment across occupations. For example, within-firm changes explain nearly all of the overall drop in employment in skilled industrial workers, but hardly none of the drop in employment in office workers, where changes in firm 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), techies, and of unskilled industrial workers.

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. We find that technology has substantial effects on firms' employment growth: techie-intensive firms grow much faster than other firms. This affects the overall composition of firms. These results also imply that technological change increases *overall* demand for labor, despite reductions in *relative* demand for some workers. 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.

Turning to within-firm changes, technology strongly increases employment shares of top managers within non-manufacturing firms, 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.

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

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.<sup>4</sup> These findings contribute to the external validity of our work.<sup>5</sup> 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.

### 1.3 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 one of the first papers to describe and analyze polarization across and within firms, and to make 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

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<sup>4</sup>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.

<sup>5</sup>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.

the U.S., and Michaels, Natraj, and Van Reenen (2014) exploit variation across industries within countries.<sup>6</sup> 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.

Goos, Manning, and Salomons (2014) is the only previous paper to have found evidence of job polarization in France, although their discussion is limited to a single line in their Table 2 and does not use data on French wages to classify occupations. Our detailed description of polarization in France allows us to give a more detailed and nuanced account of polarization in France, though our broad results are consistent with the Table 2 results of Goos *et al.* Caliendo, Monte, and Rossi-Hansberg (2015) analyze within-firm occupational change in France with the same data that we use, but they restrict their attention to manufacturing firms (25% of private sector hours) and do not discuss polarization *per se*.

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 disaggregate 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 the wage bill share of skilled workers in this period, and most of this driven by exporting plants. This led to opposing conclusions about the relative roles of trade versus technology in driving the same relative demand shift.

We are aware of only two other papers that study polarization using comprehensive matched worker-firm data.<sup>7</sup> The closest paper to ours is Kerr, Maczuskij, and Maliranta (2015), who study

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<sup>6</sup>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 find large effects of imports from China on employment and wages.

<sup>7</sup>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. Fonseca, Lima, and Pereira (2015) use matched employer-employee data to study within and between industry polarization in Portugal.

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.

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 common 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.<sup>8</sup> Our results broadly support the importance of the “routinization hypothesis”.

Our findings on the importance of techies for overall employment growth, while substituting for some occupations, are consistent with Graetz and Michaels (2016), who find that industries that invested more in robotization reduced relative demand for workers who are close substitutes to robots, but overall increased labor demand—relative to industries that adopted less robots. As they do, we interpret this finding through a product demand mechanism: the main effect of technological change, however biased, is to lower prices and increase competitiveness, which boosts

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<sup>8</sup>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.

employment demand. This theme is echoed also in Goos, Manning, and Salomons (2014) and Gregory, Salomons, and Zierahn (2016), where differential routinization can increase overall labor demand within economic units (industries and local labor markets, respectively) that are more prone to routinization, through a similar competitive effect.<sup>9</sup>

A second force that could help explain job polarization is offshoring, where domestic labor is replaced by labor abroad within and/or between firms (see among many others Feenstra and Hanson (1996), Grossman and Rossi-Hansberg (2008), Rodriguez-Clare (2010), and Blinder and Krueger (2013). Recent general equilibrium models of polarization include Egger, Kreckemeier, Moser, and Wrona (2016) and Cozzi and Impullitti (2016)). Empirically, our results suggest a relatively modest role for offshoring in explaining polarization. Similarly, Feenstra and Hanson (1999) estimate that imports of intermediate inputs have a small effect on relative demand for skilled labor in U.S. manufacturing from 1979 to 1990, while computers have a large effect. Michaels, Natraj, and Van Reenen (2014) come to a similar conclusion, as does Oesch (2013).<sup>10</sup>

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) shows, the 35-hour regulations were designed to *not* affect aggregate labor demand measured in hours and in fact they probably did not. 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.

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<sup>9</sup>We identify the employment growth effect from variation across firms within industries, while Goos, Manning, and Salomons (2014) and Graetz and Michaels (2016) use variation across industries. Gregory, Salomons, and Zierahn (2016) include in their analysis of geographical variation an income effect at the local labor market level.

<sup>10</sup>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.



Our work is closely related to Maurin and Thesmar (2004), who investigate changes in employment composition within French manufacturing from 1984 to 1995. Using survey data, they find that employment in product design and marketing increases, while employment in production drops—both for high and low-skilled workers within these categories (*qualifies* and *non-qualifies*, respectively). Concurrently, employment in high-skill administrative jobs declines. Maurin and Thesmar (2004) associate these changes to technological change. Using firm level data from 1988 to 1992, Maurin, Thoenig, and Thesmar (2002) find evidence that increases in employment in product design and marketing within French manufacturing firms may be related to exporting.<sup>11</sup>

A key objective of our 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 propensity 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 initial 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.<sup>12</sup> 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

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<sup>11</sup>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.

<sup>12</sup>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 reconcile the seemingly different predictions of Autor and Dorn (2013).

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

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 from 1970 to 1993. Using survey data, they estimate that changes in industrial composition—not technological change or globalization—drive this decline.<sup>13</sup> 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 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.

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<sup>13</sup>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 (2015).

## 1.4 Roadmap to the paper

Our paper has two types of empirical findings, descriptive and econometric. After describing the data in Section 2, we document the polarization of the French labor market, and how polarization has evolved both within and between firms, in Section 3. This section also introduces new measures of how workers in a given occupation are exposed to trade and to workers in different occupations. In Section 4 we present a simple model of firm-level technology which is used to motivate the econometric analysis in Section 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, including the widespread adoption of broadband internet, 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.<sup>14</sup> 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 our data includes all private sector French workers except the self-employed.<sup>15</sup> Our unit of analysis is annual hours paid in a firm, by occupation.<sup>16</sup> For each worker, the DADS reports gross and net wages, hours paid, occupation, tenure, gender and

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<sup>14</sup>The Socialist President Francois Mitterand left office in Spring 1995 with a National Assembly controlled by the right and center-right government of Édouard Balladur until 1997. During 1997–2002 Lionel Jospin’s left-wing government cohabitated with center-right president Jacques Chirac. During 2002–2007, both the presidency and government in France were composed by the center-right.

<sup>15</sup>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.

<sup>16</sup>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.

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.<sup>17</sup> Throughout the paper, 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.<sup>18</sup> 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, of whom 85% are in non-manufacturing (the corresponding figure for the entire firm sample is a close 86%). The permanent firms represent about a quarter of firms and half of hours paid in our sample in each year.<sup>19</sup> Changes in occupational shares (to which we turn next) within "permanent" firms are quite similar to changes in the full 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.<sup>20</sup> Excluding agricultural and public sector categories, the PCS has 22 occupational categories, listed in Table 1.<sup>21</sup> These 22 categories are consistently defined over our period of analysis.<sup>22</sup> 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

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<sup>17</sup>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*.

<sup>18</sup>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.

<sup>19</sup>These and other descriptive statistics about our sample are reported in the appendix.

<sup>20</sup>PCS stands for "Professions et Catégories Socioprofessionnelles".

<sup>21</sup>We also exclude a very small category first introduced in 2002, PCS 31, and allocate these workers to PCS 34.

<sup>22</sup>There are some small discontinuities in how workers are assigned to occupations between 2001 and 2002. See the appendix for a description of how we cope with this issue.

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 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 central to our research: PCS 38 “Technical managers and engineers” and PCS 47 “Technicians”. We refer to workers in these two occupations as “techies”. 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 even if they do not work with ICT these are jobs that require technical training, skill, and experience. As discussed in Section 1.1 above, techies mediate the effects of new technology within firms: they are the ones who plan, purchase, and install new ICT equipment, and who train and support other workers in the use of ICT. Inspection of Table 2 supports this argument, though the table also makes it clear that not all of the workers in PCS 38 and 47 necessarily work primarily with ICT. In short, if a firm invests in ICT, it needs techies, and firms with more techies are probably more technologically sophisticated firms.

The techie share of hours as a measure of firm-level technological sophistication can be compared to R&D expenditures, a common metric for technology adoption in the literature. Firm-level R&D is a useful measure, but it excludes much of the ongoing expenditure and managerial attention that firms devote to technology adoption and ICT use. In fact, reported R&D is surely not even a necessary condition for technology adoption. Conversely, R&D is likely to be impossible without the employment of techies. Thus, the techie share is a more comprehensive measure of firm-level effort devoted to technology adoption than R&D expenditures.

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 more than 99% of the hourly services supplied by techies are obtained in-house rather than purchased from consultants.<sup>23</sup>

Our analysis of job polarization uses PCS codes directly, rather than than trying to group occupations into categories such as "routine manual" and "non-routine analytic", as pioneered by Autor, Levy, and Murnane (2003). The descriptions in Table 2 obviate the need to make problematic decisions about how to map job characteristics to occupational titles.

### 2.3 Matched firm-trade

Our source for firm-level trade data is the French Customs.<sup>24</sup> For each trade observation, we know the importing or exporting firm, trading partner country, the product traded, and the value of trade. We use the firm-level SIREN identifier to match the trade data to the DADS Poste data on employment. This match is not perfect: we fail to match about 11 percent of imports and exports to firms. The reason for the imperfect match is that there are SIRENs in the trade data for which there is no corresponding SIREN in the DADS Poste. This is likely to lead to a particular type of measurement error: for some firms, we will observe zero trade even when true trade is positive.

## 3 Descriptive results

In this section we do three 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; and (3) Calculate the extent to which polarization has been a force that increases wage inequality.

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:

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<sup>23</sup>We refer to the IT consulting sector as industry code 72 in the NAF classification, which includes the following sub-categories: Hardware consultancy, Publishing of software, Other software consultancy and supply, Data processing, Database activities, Maintenance and repair of office, Accounting and computing machinery, and Other computer related activities.

<sup>24</sup>The appendix gives the details about the match between the French Customs and the DADS Poste datasets.

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

### 3.1 Occupational polarization and the *March of the Techies*

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.<sup>25</sup> 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

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<sup>25</sup>This ranking is stable over time, and insensitive to defining wages as gross or net of payroll taxes.

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.

These 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.<sup>26</sup>

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

Figure 5 shows that 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) shrink proportionately.

### 3.1.1 Polarization within and between firms

To better understand the patterns just illustrated, we turn next to a more detailed analysis of the changes in hours shares: how big were these dramatic changes, and did they occur due to within-firms adjustment, changes in firm size composition, or both? The change in the share of hours in occupation  $o$  in the economy  $S_{ot}$  can be decomposed into changes in the size of firms  $\lambda_{ft}$  with different  $s_{fot}$  ("between", or composition changes) and changes in  $s_{fot}$  within firms as follows,

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

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<sup>26</sup>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.



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

Begin by looking at the full period for all firms, which is illustrated in Figure 6 and reported in the first four columns of Table 3. Both top managerial categories grew a lot, but technical managers (PCS 38, +2.0pp) grew more 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 low skill 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 (mostly due to the decline in manufacturing as a whole). 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 (if not shrinkage). This makes it difficult to argue that the aggregate relative shift towards skilled industrial workers happens due to substitution within economic units.

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.

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 within and between industries**

Previous analyses of changes in occupational shares including Michaels, Natraj, and Van Reenen (2014) and Goos, Manning, and Salomons (2014) have looked at within-between decompositions at the level of industries. For comparability with these earlier studies, we aggregate our firm level data to 59 industries, and report a within-between industry analysis in Table 4, which has the same layout as Table 3.<sup>27</sup>

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<sup>27</sup>The number of industries analyzed in Table 4 is 59, compared to 27 in Michaels, Natraj, and Van Reenen (2014) and 21 in Goos, Manning, and Salomons (2014).

Comparing Tables 3 and 4 shows that there is a great degree of between-firm reallocation that is obscured when aggregating to the level of industries. In Table 4, almost all of the variation is within industries. For example, looking at PCS 46 Middle Managers (the largest occupation in the economy), the overall 1994-2007 decline of 1.51 percentage points is entirely between firms (-1.52) even as the industry-level analysis shows that 80 percent of the change (-1.23) occurs within industries. The conclusion is that much of the change in occupational shares occurs between firms within industries. There is nothing puzzling about this finding, but it does illustrate the importance of accounting for firm-level heterogeneity within industries when analyzing the mechanisms behind polarization.

### 3.1.3 Polarization and firm entry/exit

As noted above, entry and exit of firms is accounted for by changes in the firm employment shares  $\lambda_{ft}$  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 all other firms as  $O$ , the decomposition in (1) can be re-written as

$$\Delta S_{ot} = \underbrace{\sum_{f \in P} \Delta \lambda_{ft} \bar{s}_{fo}}_{\text{between } P} + \underbrace{\sum_{f \in P} \bar{\lambda}_f \Delta s_{fot}}_{\text{within } P} + \underbrace{\sum_{f \in O} \Delta \lambda_{ft} \bar{s}_{fo} + \sum_{f \in O} \bar{\lambda}_f \Delta s_{fot}}_{\text{other firms, net entry}}. \quad (2)$$

The set  $O$  includes firms that reported positive hours in 1994 and 2007, but zero hours in at least one year in between. Table 5 reports the results of the decomposition in (2), separately for non-manufacturing and manufacturing firms.<sup>28</sup> 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.

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<sup>28</sup>Table 5 omits occupations that amounted to less than 3 percent of sectoral hours in 2002

### 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 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:

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

where  $S_{ot}$  is the hours share of occupation  $o$ ,  $w_{ot}$  is the average wage of occupation  $o$ , and  $\bar{w}_t$  is the overall average wage.<sup>29</sup> 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 143% of the actual increase in occupational inequality from 1994 to 2007. In the second calculation we fix employment shares in 1994 and let relative wages evolve as in the data. We find that changes in occupational wages contribute -14% of the actual increase in occupational inequality from 1994 to 2007, and implies that polarization contributed 114% of the change. 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 1.3.

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<sup>29</sup>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  $w_{ot}/\bar{w}_t$  series between 2001 and 2002, as described in the appendix.

## 4 Techies, employment growth and polarization: an illustration

Our hypothesis is that techies are a channel through which falling ICT prices cause polarization. In this section we illustrate this in a simple model of firm-level outcomes. The model shows how a drop in the price of ICT can lead to (1) greater employment growth in ICT-intensive firms, and (2) polarization of employment within a firm. These results help motivating our within and between-firm econometric analysis in the following sections, and also the descriptive within and between-firm analysis above.<sup>30</sup> 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  $\widetilde{C}$ ,

$$\begin{aligned} \widetilde{M} &= \left[ \theta^{\frac{1}{\eta}} \widetilde{C}^{\frac{\eta-1}{\eta}} + (1 - \theta)^{\frac{1}{\eta}} M^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \\ \widetilde{H} &= \left[ \theta^{\frac{1}{\sigma}} \widetilde{C}^{\frac{\sigma-1}{\sigma}} + (1 - \theta)^{\frac{1}{\sigma}} H^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} . \end{aligned}$$

$\widetilde{M}$  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  $\theta$ , 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

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<sup>30</sup>Goos, Manning, and Salomons (2014) show how a within and between decomposition of the type we conduct above can be embedded in a model of the economy—but they apply this at the industry level.

paid a rental rate of  $r$ . The unit cost function corresponding to this technology is

$$b = (w_L)^{1-\alpha-\beta} (\tilde{p}_M)^\alpha (\tilde{p}_H)^\beta ,$$

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

$$\begin{aligned} \tilde{p}_M &= \left[ \theta p_C^{1-\eta} + (1-\theta) w_M^{1-\eta} \right]^{\frac{1}{1-\eta}} \\ \tilde{p}_H &= \left[ \theta p_C^{1-\sigma} + (1-\theta) w_H^{1-\sigma} \right]^{\frac{1}{1-\sigma}} , \end{aligned}$$

and the price of ICT services is

$$p_C = w_T + r .$$

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

$$\begin{aligned} \frac{H}{L} &= \frac{\beta}{1-\alpha-\beta} \left( \frac{(1-\theta) p_C^{\sigma-1} w_L}{\theta w_H^\sigma + (1-\theta) p_C^{\sigma-1} w_H} \right) \\ \frac{M}{L} &= \frac{\alpha}{1-\alpha-\beta} \left( \frac{(1-\theta) p_C^{\eta-1} w_L}{\theta w_M^\eta + (1-\theta) p_C^{\eta-1} w_M} \right) \\ \frac{H}{M} &= \frac{\beta}{\alpha} p_C^{\sigma-\eta} \left( \frac{\theta w_M^\eta + (1-\theta) p_C^{\eta-1} w_M}{\theta w_H^\sigma + (1-\theta) p_C^{\sigma-1} w_H} \right) . \end{aligned}$$

A key parameter in the technology just described is  $\theta$ , the distributional parameter associated with ICT services. The share of ICT services in total cost is increasing in  $\theta$ . This implies that the employment of techies is also increasing in  $\theta$ . This motivates our focus on techies as a marker of technology intensity in the econometric analysis below.

## 4.2 Techies, competitiveness and total employment

We first discuss the between-firm effect of falling ICT 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  $\theta$ ) 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. This competitive effect can also lead to greater employment growth in ICT-intensive (or techie-intensive) firms—and this motivates our firm employment growth regressions below.

### 4.3 Techies and polarization within firms

We now turn to the effect of falling ICT prices on relative employment within firms. As a first step, we show that 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  $L$ ,

$$\begin{aligned}\frac{\partial}{\partial r} \left( \frac{H}{L} \right) &< 0 \\ \frac{\partial}{\partial r} \left( \frac{M}{L} \right) &> 0 \\ \frac{\partial}{\partial r} \left( \frac{H}{M} \right) &< 0.\end{aligned}$$

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  $M$ .

The key question—which helps motivate our within-firm regression analysis below—is whether 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  $\alpha$  and  $\beta$  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 measures the cost of computer capital  $r$ , while the horizontal axis measures the parameter  $\theta$ . 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  $\theta$ : 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  $\theta$  on  $H/M$  is ambiguous: for low levels of  $r$  (at the bottom of the figure), higher  $\theta$  is associated with higher  $H/M$ , but for higher values of  $r$  the effect is reversed.

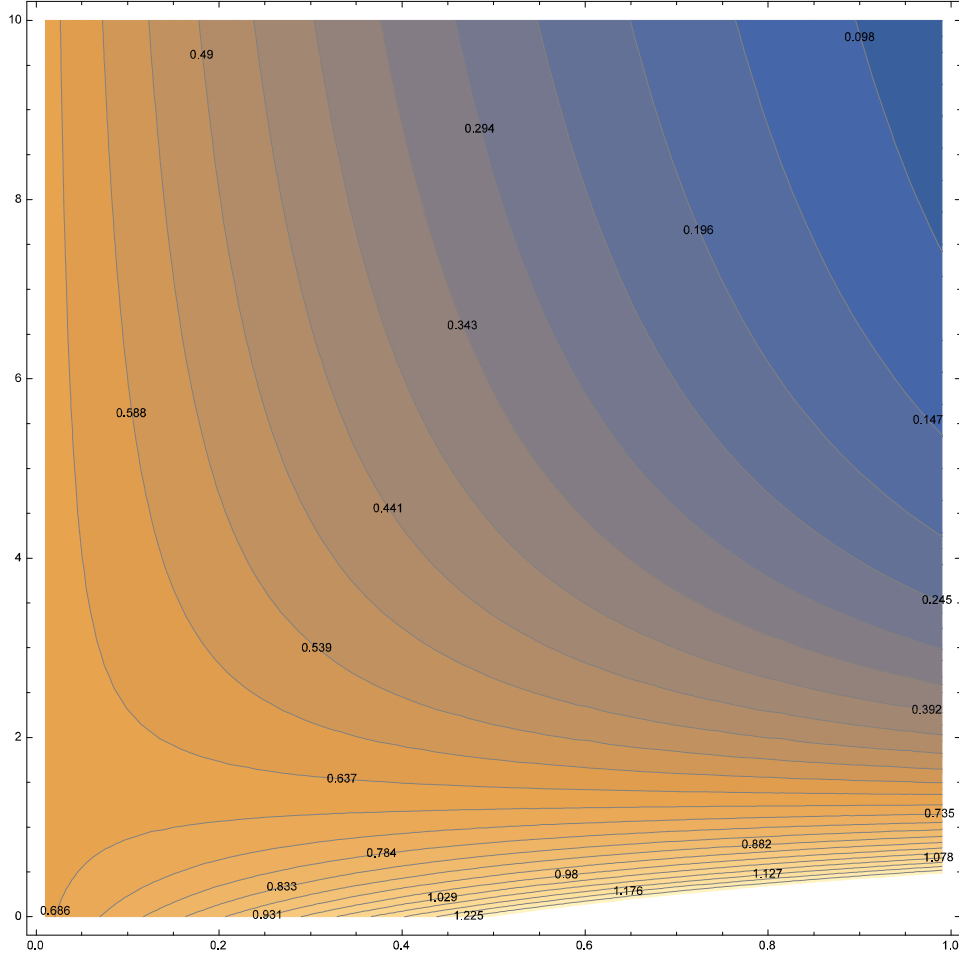


Figure 1:  $H/M$  as a function of  $r$  (vertical axis) and  $\theta$  (horizontal axis)

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 we illustrate that this effect is likely to be stronger in high- $\theta$  firms. There are three effects of falling  $r$  on the total demand for labor in high- $\theta$  firms relative to low- $\theta$  firms. The first is the competitiveness effect, which will raise the relative output of high- $\theta$  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.



## 4.4 Imports and exports

The model above is silent on globalization as an influence on the level and composition of employment. Rather than incorporate 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.<sup>31</sup> We estimate 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

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 here we quantify their importance.

### 5.1 Estimating equations

Optimal firm-level employment depends on both demand and cost conditions. We specify optimal log employment for firm  $f$  in year  $t$ ,  $\ln h_{ft}$ , as

$$\ln h_{ft} = \beta_f + D_f \cdot t + \sum_k \beta_k x_{kft} + \varepsilon_{ft} . \quad (4)$$

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<sup>31</sup>Grossman and Rossi-Hansberg (2008) show how this second effect may or may not dominate in general equilibrium.

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 (4) 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  $\varepsilon_{ft}$ .

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  $\beta_i$ .<sup>32</sup>

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,

$$\Delta \ln h_{ft} = \beta_i + \beta \mathbf{X}_{ft-1} + \beta_7 h_{ft-1} + u_{ft} . \quad (5)$$

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 (5) allows us

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<sup>32</sup>To be precise, we define an indicator function equal to 1 if firm  $f$  is in industry  $i$ . The parameter  $\beta_i$  is the coefficient that multiplies this indicator.

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  $\beta_i$ , the six parameters of interest  $\{\beta_1, \dots, \beta_6\}$  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  $\beta_i$ . We estimate (5) on a single 5-year difference from 2002 to 2007, so  $t = 2007$  and  $t - 1 = 2002$ .

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

$$\begin{aligned} \Delta \ln h_{ft} = & \beta_i + \beta_1 \text{techies}_{ft-1} + \beta_2 \text{techpos}_{ft-1} \\ & + \beta_3 \text{exports}_{ft-1} + \beta_4 \text{exppos}_{ft-1} + \beta_5 \text{imports}_{ft-1} + \beta_6 \text{imppos}_{ft-1} \\ & + (\beta_7 \text{exports}_{ft-1} + \beta_8 \text{exppos}_{ft-1} + \beta_9 \text{imports}_{ft-1} + \beta_{10} \text{imppos}_{ft-1}) \times \text{techies}_{ft-1} \\ & + (\beta_{11} \text{exports}_{ft-1} + \beta_{12} \text{exppos}_{ft-1} + \beta_{13} \text{imports}_{ft-1} + \beta_{14} \text{imppos}_{ft-1}) \times \text{techpos}_{ft-1} \\ & + \beta_{15} h_{ft-1} + u_{ft} . \end{aligned} \tag{6}$$

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 Vandebussche (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 (5) and (6) 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  $\text{exports}_{ft-1}$  and  $\text{imports}_{ft-1}$  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 (5) and (6) 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 (5) and (6) 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 data reclassification. Consequently, we estimate equations (5) and (6) 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 (5) and (6) 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, 70% 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 7 illustrates the differences between the French private sector as a whole and our estimation sample of permanent firms. For most occupations, the differences are small and stable over time, and the exceptions are small occupations. Figure 8 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 must be both strong in the first stage and exogenous in the second. We address these requirements here, but in summary: our instruments are undoubtedly strong, but there are some concerns about exogeneity. More details on our procedure for choosing instruments are in the appendix.

**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? 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). We implement two series of tests.

First, we use a sequence of “difference-in-Sargan” tests to determine the number of valid instruments.<sup>33</sup> We assume that the 1994 lag is a valid instrument, then sequentially add more recent lags (1995, 1996, etc.). The test indicates that in non-manufacturing 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. We chose the average of five lags, 1994–1998, in both sectors for symmetry.<sup>34</sup> Second, we use the procedure proposed by Donald and Newey (2001) to determine the optimal number of valid instruments.<sup>35</sup> The Donald and Newey (2001) procedure suggests using six or seven lags as instruments. To be conservative, we use the smaller set of instruments dictated by the difference-in-Sargan procedure.

**Are the instruments strong?** 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)). In the absence of critical values for a first stage  $F$  test, we instead report Shea (1997)’s partial  $R^2$ .<sup>36</sup> The Shea partial  $R^2$ s for equation (5) are reported in Table 6, and the

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<sup>33</sup>For the “difference-in-Sargan” test see Hayashi (2000), pages 218–221 and 232–234, and Ruud (2000), Chapter 22.

<sup>34</sup>Test results are available upon request.

<sup>35</sup>The Donald-Newey procedure chooses, from a group of valid instrument, the set that minimizes the mean-squared error (MSE) of the estimator. Of the two minimum MSE criteria proposed by Donald and Newey (2001), we use the Mallows criteria, which proves to be computationally more robust.

<sup>36</sup>Since our application includes seven endogenous regressors, there is no econometric theory available to guide the choice of critical values for the conventional first stage  $F$  statistic. The Shea’s statistic, along with other measures of

results leave no doubt that the first stage is strong.

**Are the instruments exogenous?** For the instruments to be exogenous, they must be uncorrelated with the composite error term  $u_{it}$  in (5). Recall that  $u_{it}$  includes both changes in firm characteristics  $x_{kft}$  and changes in the error term  $\varepsilon_{ft}$  in (4). Thus our identifying assumption is that five year *changes* in the  $x_{kft}$ 's and the error term  $\varepsilon_{ft}$  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. We perform several specification tests. We first 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. Second, we use a procedure where we add the 1998 lag of techies, trade, and employment to (5), using lags from 1994 to 1997 as instruments. We then test the null hypothesis that the coefficients on the 1998 levels are jointly zero. This null cannot be rejected, which leads us to proceed in assuming that the exclusion restrictions for lags from 1994 to 1998 are valid.

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 intermediate inputs 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  $\varepsilon_{ft}$  in (4). In the appendix we show that although serial correlation in  $\varepsilon_{ft}$  does give rise to bias, this bias is likely to be small.

A more serious concern is omitted variables in initial period levels in equation (5).<sup>37</sup> Potentially important omitted variables include other firm inputs such as capital. 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*.

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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.

<sup>37</sup>This amounts to a misspecification of the  $D_f$  function.

Table 7 reports  $p$ -values for two standard diagnostic tests for 2SLS estimation of equation (5). 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.<sup>38</sup> 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 employment. Since the distribution of employment across firms is highly skewed, unweighted regression analysis of (5) 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.<sup>39</sup>

### 5.2.3 Summary of estimation strategy

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

- 2 regressions, manufacturing and nonmanufacturing firms
- Dependent variable is growth in hours, 2002-2007
- Explanatory variables are levels of techies (share of hours), trade (imports and exports, scaled by total firm wage bill), and log hours in 2002
- Estimator is weighted two stage least squares
- Instruments are lagged techies, trade, and log hours 1994-1998
- Observations weighted by firm hours in 2002

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<sup>38</sup>There are seven degrees of freedom for the Hausman test because there are seven endogenous variables in (5). 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.

<sup>39</sup>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).

- Heteroskedasticity robust covariance matrix.

### 5.3 Estimation results

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

1. What is the effect of an increase from zero to the median of the explanatory variable on the growth in hours? We call this the *extensive margin effect*.
2. What is the effect of an increase from the 25<sup>th</sup> to the 75<sup>th</sup> 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<sup>th</sup>-25<sup>th</sup> percentile range (also called the interquartile range or IQR) of the growth in hours.<sup>40</sup> Computing these effects involves calculating the estimated conditional mean at two different points, and then looking at the difference. For equation (5), the formulas for the extensive and intensive margin effects of techies on occupation  $o$  are, respectively,

$$extensive\_techies = \frac{\hat{\beta}_2 + \hat{\beta}_1 \times p50(techies)}{p75(\Delta \ln h_{ft}) - p25(\Delta \ln h_{ft})} \quad (7)$$

$$intensive\_techies = \frac{\hat{\beta}_1 \times [p75(techies) - p25(techies)]}{p75(\Delta \ln h_{ft}) - p25(\Delta \ln h_{ft})} \quad (8)$$

where  $pN(x)$  is the  $N^{th}$  percentile of variable  $x$ . Analogous definitions apply to the intensive and extensive margin effects of imports and exports. 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 quite similar to elasticities.

The interaction effects estimated in equation (6) permit us to refine the above questions. In particular, we can ask: what are the intensive and extensive margin effects of techies among firms that trade and those who do not trade? Similarly, we can ask: what are the intensive and extensive margin effects of imports and exports among firms with and without techies? As with the simpler formulas given by (7) and (8), the formulas for the differences in conditional means involve both

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<sup>40</sup>For the explanatory variables, in computing the intensive and extensive margin effects we use the percentiles of the distribution of strictly positive values.



parameter estimates and percentiles of the data. The somewhat involved expressions for these effects are relegated to the appendix, as are the parameter estimates for equations (5) and (6). Tables 8 and 9 report the size of relevant subsamples.<sup>41</sup>

### 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).

- 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 among firms that do not trade (column 3, almost 60% of employment within nonmanufacturing), and there is also a small 0.15 intensive margin effect for these firms (column 4). Among firms that trade (column 5), the extensive margin effect is not significant, and there is a small negative intensive margin effect (column 6).
- Techies have a strong effect on manufacturing employment growth, with an extensive margin effect of 0.94 and an intensive margin effect of 0.22 (columns 1 and 2). The extensive margin effect is particularly strong among firms that do not trade (column 3), and is positive but not significant among firms that do trade (column 5). The fact that the extensive margin effect of techies is imprecisely estimated within the set of firms that trade is due to the fact that almost all trading firms employ techies (Table 8).

Overall, Panel A of Table 10 shows that firms that employed techies in 2002 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. These findings are consistent with those in Graetz and Michaels (2016), Goos, Manning, and Salomons (2014) and Gregory, Salomons, and Zierahn (2016), who also estimate increases in overall labor demand within economic units (industries or local labor markets) that undergo differentially more technological change through a similar competitive effect.

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<sup>41</sup>Because firms that only import or only export comprise such a small share of hours worked (16 percent of hours in nonmanufacturing, 9 percent in manufacturing) and of trade (10 percent of trade in nonmanufacturing, 1 percent in manufacturing), we do not report the estimated effects for these firms. Complete results are reported in the appendix.

### 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. 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 (5) that disaggregate trade, first by separating 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). As in all our other specifications, these import measures enter the regression 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:

- Panel A shows that neither importing nor exporting have statistically significant effects for nonmanufacturing firms.
- Panel B, Column 3 shows that for manufacturing firms, importing *per se* has a statistically insignificant positive extensive margin effect, but the extensive margin of imports of intermediates is large and negative, at -0.8. The negative employment growth effects of importing intermediate inputs (that is, offshoring) is suggestive of a simple substitution effect of foreign for domestic labor, which is also what we find in Table 17 below.
- When distinguishing imports by source country (Panel B, columns 5 and 6), we find that 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 countries), 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 by manufacturing firms (Panel B) has no detectable effect on employment growth in any specification (the extensive margin effects are small and positive and the intensive

margin effects are small and negative, but none are precisely estimated). Experimentation with distinguishing exports by destinations or by intermediate classification (not reported) yield the same conclusion.

Overall, the results in Table 11 imply large labor substitution due to offshoring, particularly to low income countries, that are restricted to manufacturing firms. Since nonmanufacturing firms are usually not engaged directly in international trade, finding no effects of trade there is not surprising.

## 6 Econometric analysis of within firm changes in occupational structure

The broad research question of this section is: what explains changes in the occupational structure of French firms, and in particular the job polarization that was documented above? Our hypothesis is that both globalization and technological change are important causal factors, and the purpose of our econometric analysis is to quantify their importance. We measure changes in a firm’s occupational structure by changes in the share of hours in one of twelve PCS occupations, excluding the share of techies (PCS 38 and 47). Changes in this “ex-techie” share are explained by firm-level measures of exposure to globalization (imports and exports as a share of the firm’s wage bill) and technology (the share of techies in 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  $\Delta s_{fot}$ , the ex-techie share of hours of the twelve large non-techie occupations listed in Table 2 (each one accounting for at least three percent of hours in 2002). For each occupation  $o$  (in each sector) our estimating equation is

$$\Delta s_{fot} = \beta_i^o + \beta^o \mathbf{X}_{ft-1} + u_{ft}^o, \quad (9)$$

where  $\mathbf{X}$  includes the same regressors as in equations (5) and (6) with the exception of log total hours.<sup>42</sup> We estimate (9) separately for manufacturing and nonmanufacturing. The estimator is again weighted 2SLS, where the weights are 2002 hours. The issues of instrument strength and validity are the same as before. 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.

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<sup>42</sup>Adding log total hours to (9) hardly affects the estimates reported below. Invariably across occupations, log total hours has a small and statistically significant effect on changes in occupational shares.

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 year, and the weighted median number of occupations per firm-year is 10.<sup>43</sup> This means that when estimating (9) the sample size varies by PCS code.<sup>44</sup> 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 sample selection.

## 6.2 Estimation results

As in Section 5, we report scaled effects rather than regression coefficients. Tables 14 through 17 report our results.<sup>45</sup> 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 (9). The remaining columns are functions of the data and the estimated parameters of the interaction specification. Statistically significant effects are shaded, and standard errors are reported in italics.

### 6.2.1 Techies cause within-firm skill upgrading in nonmanufacturing

Turning first to the estimates for nonmanufacturing firms, the *Overall* results in Table 14 show that techies have a large positive effect on within-firm skill upgrading:

- Firms with more techies have statistically significantly higher employment growth of top managers (PCS 37), and the effect is large. The extensive margin effect, which compares a firm with no techies to one with a median techie share, is that the latter has growth in the managerial share of hours that is higher by 34% of the interquartile range (IQR). Turning to the intensive margin effect among firms with techies, the effect of a one IQR higher techie share is to raise growth of the managerial share by a fifth of its IQR.
- Among other white collar workers, the intensive margin effect of techies is to cause modest skill upgrading: middle-management jobs grow faster (PCS 46, effect is +0.048) while low-paid office and retail occupations grow more slowly (the effect for Office Workers PCS 54 is -0.055, and for Retail Workers PCS 55 it is -0.15).

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<sup>43</sup>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.

<sup>44</sup>When  $s_{fot} = s_{fot-1} = 0$ , we treat the change  $\Delta s_{fot}$  as undefined, and firm  $f$  is not included in the estimation sample for occupation  $o$ .

<sup>45</sup>For each sector, we include estimates only for occupations that amounted to at least 3 percent of hours in 2002.

- 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.<sup>46</sup>
- The final 4 columns of Table 14 shows how the effect of techie varies with firm’s trading status:
  - For firms that do not trade (58 percent of hours in nonmanufacturing, Table 8), the extensive margin effect of techies on top manager growth (PCS 37) is half of the IQR. There are no statistically significant effects for other white collar occupations (PCs 46 to 56), but there is a strong skill upgrading effect within blue collar workers, particularly along the extensive margin: techies cause faster growth for skilled industrial (PCS 62, +1.4) and transport/logistics workers (PCS 65, +0.7), and slower growth for low-skill manual laborers (PCS 68, -0.7).
  - For firms that both import and export (26 percent of hours), the extensive margin effects of techies in column 5 are not precisely estimated, which is a consequence of the fact that over 90 percent of hours among this group of firms are in firms with techies (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 polarization in manufacturing

Table 15 shows that rather than causing skill upgrading as they do in nonmanufacturing, techies cause polarization within manufacturing firms.

- Overall, we see in columns 1 and 2 that mid-level professionals (PCS 46, +0.56) grow at the expense of office workers (PCS 54, -0.5), skilled industrial workers’ share shrink a lot (PCS 62, -0.82), and drivers (PCS 64, +1.5) increase their shares as a residual, in a way that is consistent with the illustration in Section 4. Their intensive margins agree with the extensive ones.

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<sup>46</sup>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.

- Among manufacturing firms that do not trade, we see a similar pattern, with the addition of large effects for top managers and professionals (PCS 37, +0.83) and on the other side of the wage distribution, for low skill industrial workers (PCS 67, +1.5). This latter effects is part of a techie *skill downgrading* effects within blue collar workers (compare to -1.27 for PCS 62). The effect for clerical workers is also negative (PCS 54, -0.5) though not statistically significant.
- The extensive effects among firms that trade (columns 5 and 6, 78 percent of hours in manufacturing) are similar to the overall effects. Techies cause skill upgrading within white collar workers, with middle managers gaining shares (PCS 46, +0.64) and clerical workers losing (PCS 54, -0.87), both along the extensive and intensive margins. Skilled industrial workers (PCS 62, -0.2) lose shares, but only at the intensive margin. The effect for drivers is precisely estimated only at the intensive margin, but is consistent with the overall effect.

### 6.2.3 Trade affects within-firm skill mix in manufacturing

Tables 16 and 17 show that trade also affects the within-firm occupational mix, but mainly in manufacturing. Looking first at nonmanufacturing firms in Table 16, we see that importing has small and mainly statistically insignificant effects on the occupational mix, except for drivers (PCS 64). Compared to firms that do not export, firms that export (columns 5 and 7 of the Table 16) have sharply falling shares of office workers (PCS 54, -0.8) and rising shares of low skill manual workers (PCS 68, +2.4 or +3.4). Retail workers (PCS 55, +0.66) have higher shares in exporting firms, but only if they employ techies (column 7).

Given that nonmanufacturing firms do not engage in much direct international trade, the lack 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. The overall effect of +0.4 (column 5) is similar in size, though imprecisely estimated, among firms with techies. By contrast, importing has no extensive margin effect on the PCS 37 share.
- There is a strong blue collar skill *upgrading* effect of importing (column 1): importing increases the shares of skilled industrial and skilled manual laborers (+1.3 for PCS 62 and +6.2 for PCS 63, respectively), while reducing the share of unskilled industrial workers (PCS 67, -3.3).
- There is a strong blue collar skill *downgrading* effect of exporting (column 5): exporting reduces the share of skilled industrial and skilled manual laborers (-1.0 for PCS 62 and -3.4

for PCS 63, respectively), while increasing the share of unskilled industrial workers (PCS 67, +2.1).

The intensive margin effects of trade in manufacturing industries are mostly small and/or statistically insignificant—all the action comes from comparing firms that do not trade with firms that do. The effects for firms with techies (columns 3, 4, 7, and 8) are very similar to the overall effects, which is to be expected since virtually all manufacturing firms that trade also have techies (last line of Table 9).

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 importing is associated with declines in production workers' employment, and in particular low-skill production workers' employment in French Manufacturing in 1986–1992.

Our finding that exporting is associated with faster growth of managers (PCS 37) is not surprising, given the extensive literature that documents a positive correlation between the share of non-production/white-collar jobs and exporting. What is new and puzzling is our finding that exporting causes skill *downgrading* within production/blue-collar occupations. Together these results imply a within-firm polarizing effect of exporting. Earlier researchers using plant or firm level data could not uncover this effect because they did not have information on skill composition within production/blue-collar workers.<sup>47</sup>

## 7 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. The importance of between-firm reallocations for polarization implies that simple theories of substitution across workers within firms miss an important margin of adjustment. 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.

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<sup>47</sup>An exception is Verhoogen (2008), who 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 and finds evidence for skill upgrading due to the devaluation.

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. We develop an empirical framework that allows us to study the firm-level causal effects of falling ICT prices and the growth of offshoring and exporting.

Our econometric results 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. Offshoring—i.e., imports of intermediate inputs, mostly from low income countries—causes slower employment growth in manufacturing, while exporting has no effect on employment growth.

Our results also show that within nonmanufacturing firms with more techies in 2002 there is substantial skill *upgrading* from 2002 to 2007, with the share of hours worked by managers increasing and the share worked by office and retail workers declining. The effect of techies within manufacturing firms was polarizing: shares of mid-level professionals, low skill industrial workers and drivers increase, while shares of middle income clerical and skilled industrial workers fell. 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.

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 one of the first to analyze these economy-wide changes using firm-level data, which has made it possible to paint a rich and nuanced portrait of how and why polarization evolved in France between 1994 and 2007.



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## 8 Figures and Tables

Table 1: PCS Occupations

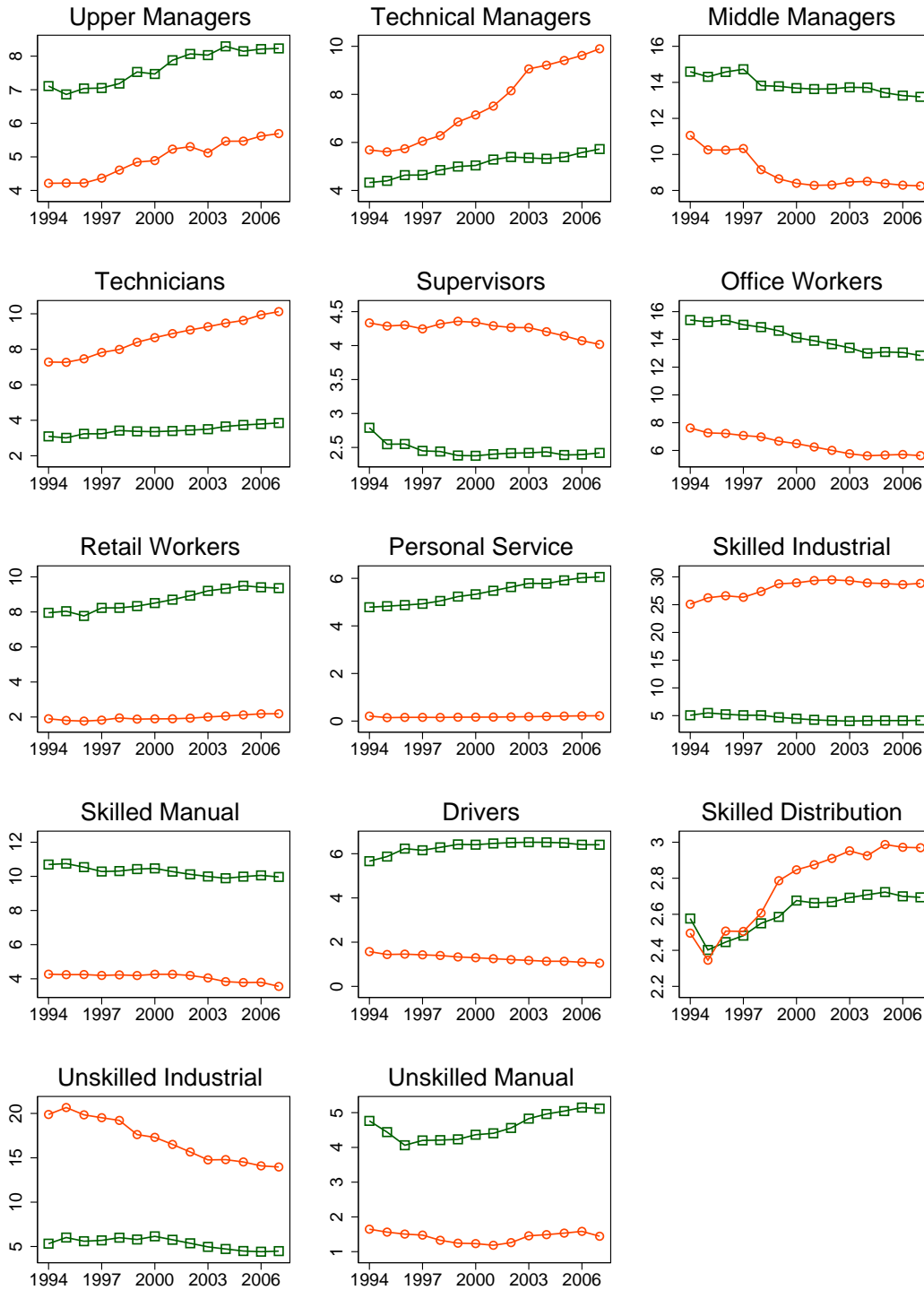
PCS code	description of occupation	rank	share
21	Small business owners and workers	7	0.1
22	Shopkeepers	3	0.2
23	Heads of businesses	1	0.7
34	Scientific and educational professionals	5	0.5
35	Creative professionals	6	0.6
<b>37</b>	<b>Top managers and professionals</b>	<b>2</b>	<b>7.3</b>
<b>38</b>	<b>Technical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

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

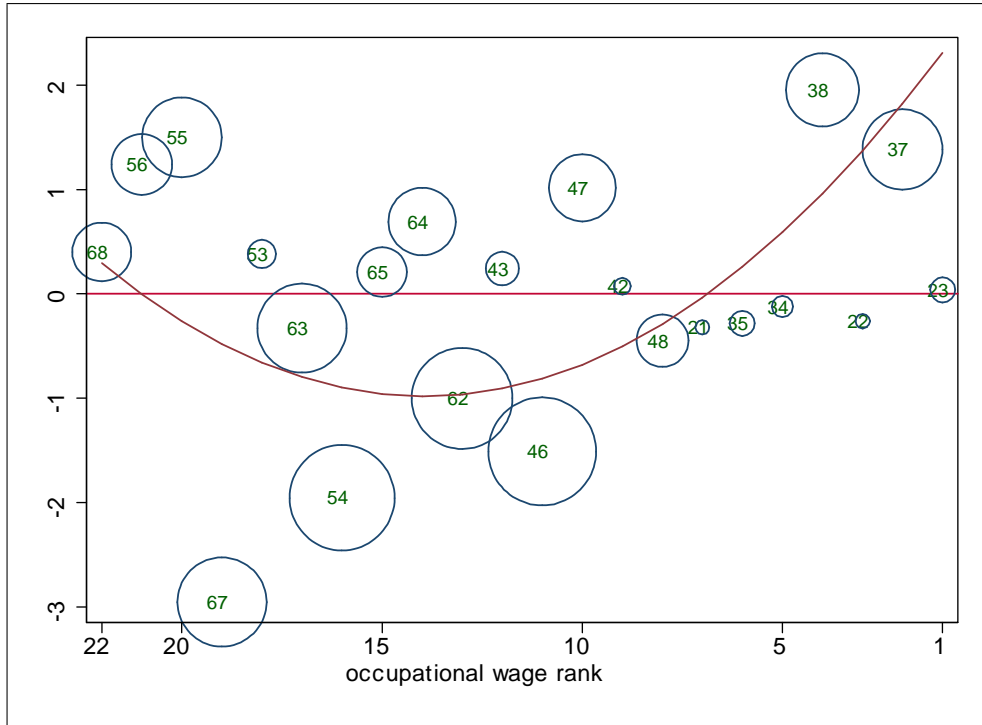
<b>37</b>	<b>Top managers and professionals</b> Managers of large businesses Finance, accounting, sales, and advertising managers Other administrative managers	<b>56</b>	<b>Personal service workers</b> Restaurant servers, food prep workers Hotel employees: front desk, cleaning, other Barbers, hair stylists,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

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<sup>2</sup>. For key to occupations, see Tables 1 and 2.



Figure 4: Change in employment shares 1994–2007, Nonmanufacturing

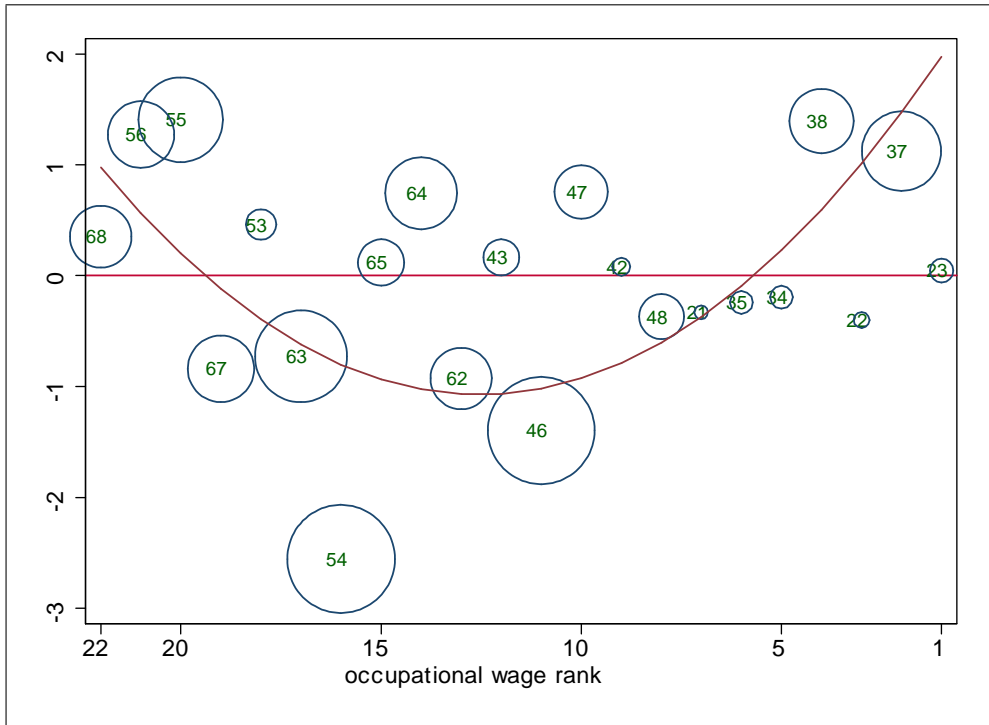


Figure 5: Change in employment shares 1994–2007, Manufacturing

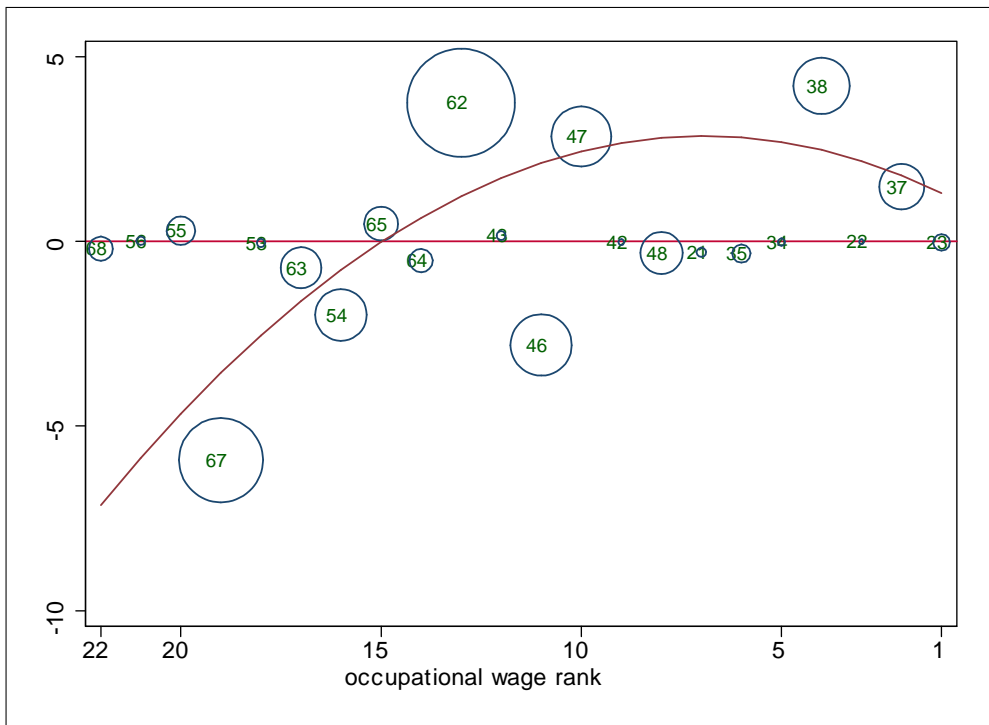
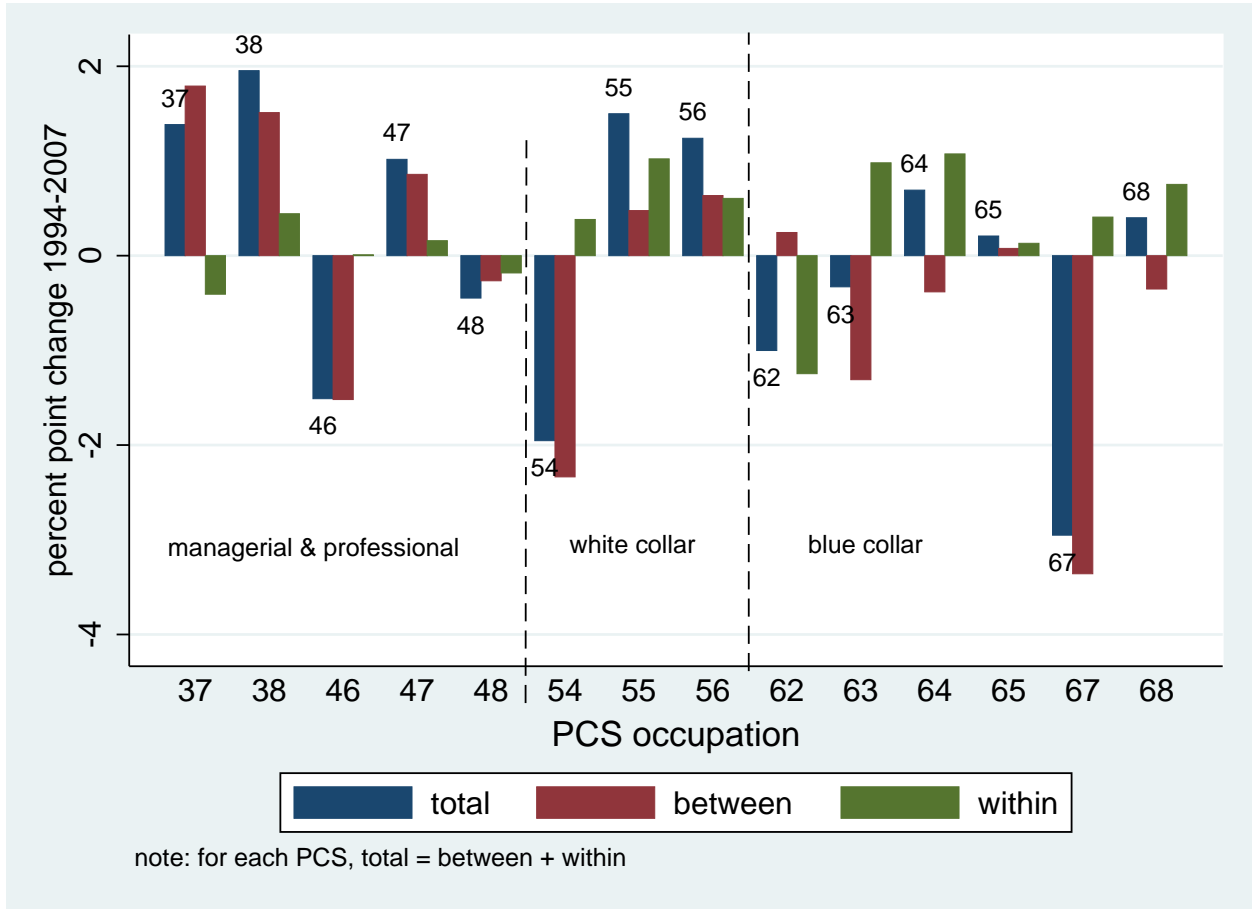


Table 3: Changes in occupational hours share: between-within firms decomposition (1994-2007)

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



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).

Table 4: Changes in occupational hours share: between-within industry decomposition (1994-2007)

Rank	PCS2	All firms						Nonmanufacturing						Manufacturing					
		Share	$\Delta$ Share	Between	Within	Share	$\Delta$ Share	Between	Within	Share	$\Delta$ Share	Between	Within	Share	$\Delta$ Share	Between	Within		
7	21	0.22	-0.320	-0.018	-0.302	0.23	-0.330	-0.015	-0.315	0.21	-0.296	-0.024	-0.272	0.21	-0.296	-0.024	-0.272		
3	22	0.23	-0.262	0.016	-0.278	0.30	-0.402	-0.020	-0.382	0.05	-0.011	-0.004	-0.007	0.05	-0.011	-0.004	-0.007		
1	23	0.67	0.038	0.004	0.034	0.67	0.045	0.003	0.042	0.68	-0.026	-0.062	0.036	0.68	-0.026	-0.062	0.036		
5	34	0.50	-0.122	0.031	-0.153	0.64	-0.194	-0.025	-0.169	0.13	-0.022	0.004	-0.026	0.13	-0.022	0.004	-0.026		
6	35	0.68	-0.283	-0.005	-0.278	0.64	-0.241	0.048	-0.289	0.81	-0.333	-0.086	-0.247	0.81	-0.333	-0.086	-0.247		
2	37	6.91	1.384	-0.173	1.557	7.65	1.122	-0.495	1.617	4.95	1.480	-0.033	1.513	4.95	1.480	-0.033	1.513		
4	38	5.75	1.954	0.198	1.756	5.07	1.394	0.512	0.882	7.59	4.211	0.095	4.116	7.59	4.211	0.095	4.116		
9	42	0.31	0.073	-0.054	0.127	0.39	0.080	-0.112	0.192	0.08	-0.020	0.002	-0.022	0.08	-0.020	0.002	-0.022		
12	43	1.20	0.242	0.093	0.149	1.58	0.166	0.009	0.157	0.20	0.156	-0.014	0.170	0.20	0.156	-0.014	0.170		
11	46	12.55	-1.510	-0.281	-1.229	13.86	-1.396	-0.689	-0.707	9.04	-2.805	-0.251	-2.554	9.04	-2.805	-0.251	-2.554		
10	47	4.85	1.017	-0.077	1.094	3.44	0.756	0.233	0.523	8.67	2.839	0.277	2.562	8.67	2.839	0.277	2.562		
8	48	2.95	-0.448	-0.118	-0.330	2.46	-0.370	-0.046	-0.324	4.25	-0.316	0.045	-0.361	4.25	-0.316	0.045	-0.361		
18	53	0.86	0.380	0.161	0.219	1.12	0.462	0.136	0.326	0.16	-0.043	0.006	-0.049	0.16	-0.043	0.006	-0.049		
16	54	12.01	-1.954	-0.056	-1.898	14.12	-2.555	-0.658	-1.897	6.43	-1.990	-0.223	-1.767	6.43	-1.990	-0.223	-1.767		
20	55	6.85	1.499	0.660	0.839	8.68	1.408	0.337	1.071	1.96	0.285	-0.030	0.315	1.96	0.285	-0.030	0.315		
21	56	3.98	1.240	0.459	0.781	5.41	1.272	0.178	1.094	0.18	0.013	-0.004	0.017	0.18	0.013	-0.004	0.017		
13	62	10.97	-1.002	-0.595	-0.407	4.57	-0.926	0.083	-1.01	28.05	3.748	0.394	3.354	28.05	3.748	0.394	3.354		
17	63	8.57	-0.329	0.281	-0.610	10.27	-0.726	-0.408	-0.318	4.08	-0.716	0.176	-0.892	4.08	-0.716	0.176	-0.892		
14	64	4.94	0.692	0.779	-0.087	6.31	0.744	0.649	0.095	1.28	-0.523	0.031	-0.554	1.28	-0.523	0.031	-0.554		
15	65	2.65	0.208	-0.090	0.298	2.61	0.118	-0.113	0.231	2.76	0.474	0.019	0.455	2.76	0.474	0.019	0.455		
19	67	8.58	-2.951	-0.757	-2.194	5.34	-0.841	0.345	-1.186	17.03	-5.916	-0.408	-5.508	17.03	-5.916	-0.408	-5.508		
22	68	3.73	0.401	0.470	-0.069	4.60	0.353	0.279	0.074	1.43	-0.202	0.015	-0.217	1.43	-0.202	0.015	-0.217		

Notes to Table 4: 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.

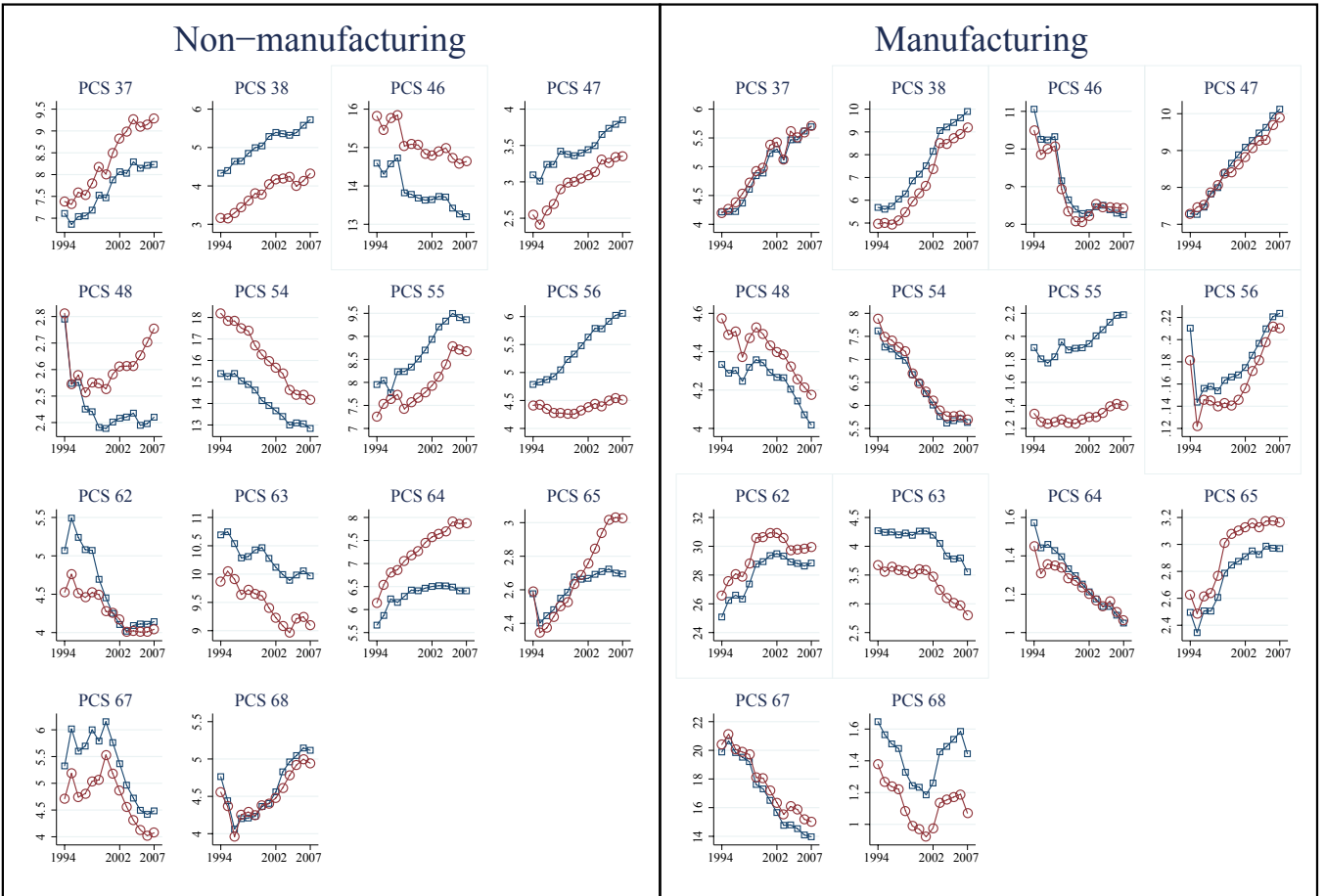


Table 5: Between-Within decomposition 1994-2007, permanent firms and net entry

PCS2	All firms		Permanent firms		All other firms		
	2002 share (1)	Change 94-07 (2)	Between-p (3)	Within-p (4)	Net entry (5)	Share of total (6)	
	<b>Non-manufacturing</b>						
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
	<b>Manufacturing</b>						
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 5:** 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 hours shares for all firms and permanent firms

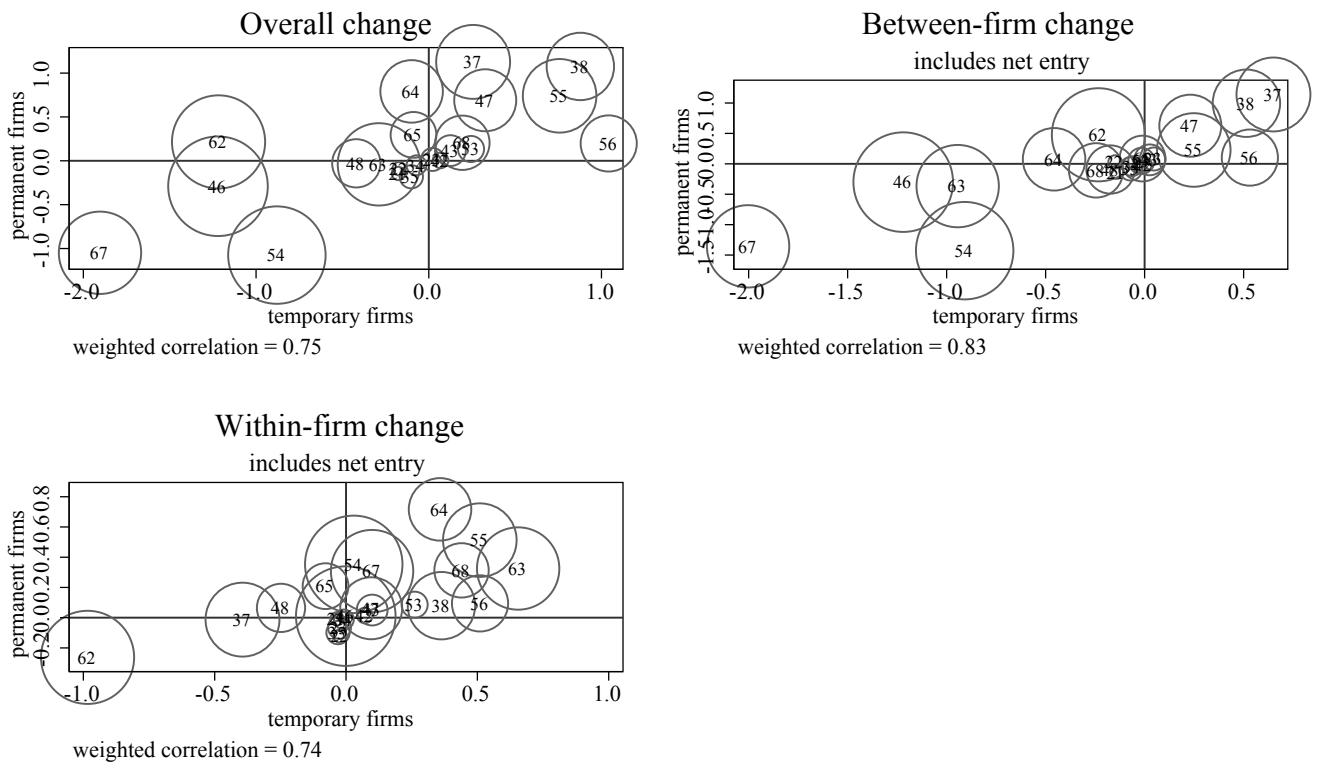


Blue box: All firms  
 Red circle: Permanent firms

Notes to Figures 7 and 8: "Permanent" firms are those with positive hours for each year from 1994 to 2007, "All" includes permanent and all other firms. In Figure 8, size of circles is proportional to occupation's hours share in 2002. For key to occupations, see Tables 1 and 2.

Figure 8: Changes in occupational hours shares

permanent vs. temporary firms



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 (5). Each number in the table is the adjusted Shea (1997) partial  $R^2$  of the first stage equation for the endogenous variable listed in the row, corresponding to the second stage equation listed in the column.

Table 7: Test statistics for baseline employment growth regressions

	Nonmanufacturing	Manufacturing
<i>p-values</i>		
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 (5).

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

techies?	nonmanufacturing					
	imports			exports		
	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

techies?	manufacturing					
	imports			exports		
	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 (1)	intensive (2)	extensive (3)	intensive (4)	extensive (5)	intensive (6)
<b>Panel A</b>						
Nonmanufacturing	0.344*	0.011	0.311*	0.153***	0.244	-0.148*
	<i>0.189</i>	<i>0.043</i>	<i>0.179</i>	<i>0.059</i>	<i>0.305</i>	<i>0.088</i>
Manufacturing	0.939***	0.219***	1.140***	0.134	0.392	0.264***
	<i>0.211</i>	<i>0.067</i>	<i>0.211</i>	<i>0.146</i>	<i>0.291</i>	<i>0.080</i>
	imports		techies		exports	
	overall extensive (1)	intensive (2)	extensive (3)	intensive (4)	overall extensive (5)	intensive (6)
<b>Panel B</b>						
Nonmanufacturing	-0.126	0.002	-0.090	0.008	-0.339	-0.279
	<i>0.218</i>	<i>0.009</i>	<i>0.372</i>	<i>0.014</i>	<i>0.218</i>	<i>0.373</i>
Manufacturing	-0.148	0.036	-0.207	0.043	0.077	0.025
	<i>0.268</i>	<i>0.039</i>	<i>0.339</i>	<i>0.044</i>	<i>0.212</i>	<i>0.280</i>
						-0.010***
						<i>0.003</i>

Standard errors italicized, \* = 90%, \*\* = 95%, \*\*\* = 99% statistical significance.

Table 11: Effects of techies, exports and different classes of imports

	extensive (1)	intensive (2)	extensive (3)	intensive (4)	extensive (5)	intensive (6)
<b>A. Nonmanufacturing</b>						
techies	<b>0.344*</b>	0.011	0.331	0.011	<b>0.400**</b>	0.015
	<i>0.189</i>	<i>0.043</i>	<i>0.203</i>	<i>0.042</i>	<i>0.180</i>	<i>0.040</i>
exports	-0.339	-0.005	<b>-0.390*</b>	-0.005	-0.179	-0.005
	<i>0.218</i>	<i>0.005</i>	<i>0.220</i>	<i>0.004</i>	<i>0.245</i>	<i>0.005</i>
imports	-0.126	0.002	-0.040	0.010		
	<i>0.218</i>	<i>0.009</i>	<i>0.330</i>	<i>0.010</i>		
imports of intermediate inputs			0.012	<b>-0.012*</b>		
			<i>0.308</i>	<i>0.006</i>		
imports from China					-0.146	0.005
					<i>0.445</i>	<i>0.006</i>
imports from high income countries					0.031	0.008
					<i>0.257</i>	<i>0.010</i>
imports from other countries					-0.373	0.001
					<i>0.357</i>	<i>0.004</i>
<b>B. Manufacturing</b>						
techies	<b>0.939***</b>	<b>0.219***</b>	<b>0.929***</b>	<b>0.221***</b>	<b>0.815***</b>	<b>0.229***</b>
	<i>0.211</i>	<i>0.067</i>	<i>0.209</i>	<i>0.067</i>	<i>0.210</i>	<i>0.069</i>
exports	0.077	-0.038	0.055	-0.031	0.182	-0.020
	<i>0.212</i>	<i>0.051</i>	<i>0.213</i>	<i>0.051</i>	<i>0.200</i>	<i>0.050</i>
imports	-0.148	0.036	0.698	0.066		
	<i>0.268</i>	<i>0.039</i>	<i>0.518</i>	<i>0.057</i>		
imports of intermediate inputs			<b>-0.815**</b>	-0.032		
			<i>0.375</i>	<i>0.046</i>		
imports from China					-0.085	0.006
					<i>0.188</i>	<i>0.005</i>
imports from high income countries					-0.010	<b>0.098**</b>
					<i>0.227</i>	<i>0.049</i>
imports from other countries					<b>-0.431**</b>	<b>-0.025**</b>
					<i>0.211</i>	<i>0.011</i>

Standard errors italicized, \* = 90%, \*\* = 95%, \*\*\* = 99% statistical significance.

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 (9). Each number in the table is the adjusted Shea (1997) partial  $R^2$  of the first stage equation for the endogenous variable listed in the row, corresponding to the second stage equation listed in the column. For key to occupations, see Tables 1 and 2.

Table 13: Second stage test statistics, baseline within regressions

<b>Nonmanufacturing:</b>					
PCS	37	46	54	55	56
<i>p</i> -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
<i>p</i> -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
<b>Manufacturing:</b>					
PCS	37	46	48	54	62
<i>p</i> -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		
<i>p</i> -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 (9).

Notes to Tables 14 through 17: The tables on the following four pages report estimated effects derived from 2SLS estimation of equations (9) (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 (1)	intensive (2)	extensive (3)	intensive (4)	extensive (5)	intensive (6)
37 Top managers and professionals	<b>0.340*</b> <i>0.182</i>	<b>0.215***</b> <i>0.082</i>	<b>0.516***</b> <i>0.160</i>	0.051 <i>0.038</i>	0.179 <i>0.436</i>	<b>0.295***</b> <i>0.108</i>
46 Mid-level professionals	-0.106 <i>0.096</i>	<b>0.048**</b> <i>0.019</i>	-0.128 <i>0.113</i>	0.019 <i>0.024</i>	0.276 <i>0.239</i>	<b>0.096***</b> <i>0.035</i>
54 Office workers	0.006 <i>0.110</i>	<b>-0.055*</b> <i>0.030</i>	-0.003 <i>0.132</i>	-0.028 <i>0.033</i>	-0.399 <i>0.284</i>	-0.094 <i>0.066</i>
55 Retail workers	0.120 <i>0.319</i>	<b>-0.153**</b> <i>0.076</i>	0.066 <i>0.372</i>	0.002 <i>0.060</i>	-0.030 <i>0.714</i>	<b>-0.251*</b> <i>0.145</i>
56 Personal service workers	-0.616 <i>0.875</i>	<b>0.130*</b> <i>0.078</i>	-0.319 <i>0.984</i>	0.161 <i>0.153</i>	-3.570 <i>2.294</i>	0.014 <i>0.157</i>
62 Skilled industrial workers	<b>1.458***</b> <i>0.596</i>	<b>-0.261</b> <i>0.213</i>	<b>1.430***</b> <i>0.433</i>	<b>0.275*</b> <i>0.162</i>	0.787 <i>1.621</i>	<b>-0.401**</b> <i>0.169</i>
63 Skilled manual laborers	0.214 <i>0.177</i>	-0.062 <i>0.051</i>	0.181 <i>0.166</i>	0.025 <i>0.102</i>	0.263 <i>0.756</i>	-0.095 <i>0.063</i>
64 Drivers	-0.080 <i>0.246</i>	<b>-0.132**</b> <i>0.057</i>	-0.108 <i>0.327</i>	<b>-0.288*</b> <i>0.150</i>	0.254 <i>0.668</i>	-0.061 <i>0.065</i>
67 Low skill industrial workers	0.220 <i>0.261</i>	<b>0.154**</b> <i>0.066</i>	0.525 <i>0.354</i>	0.100 <i>0.092</i>	<b>-1.060**</b> <i>0.524</i>	<b>0.218**</b> <i>0.088</i>
68 Low skill manual laborers	<b>-0.673***</b> <i>0.241</i>	<b>-0.199**</b> <i>0.079</i>	<b>-0.712**</b> <i>0.293</i>	-0.156 <i>0.086</i>	0.095 <i>0.115</i>	<b>-0.230**</b> <i>0.121</i>

Standard errors italicized, \* = 90%, \*\* = 95%, \*\*\* = 99% statistical significance.



Table 15: Effects of techies on employment shares in manufacturing firms

	overall		no trade		imports & exports > 0	
	extensive (1)	intensive (2)	extensive (3)	intensive (4)	extensive (5)	intensive (6)
37 Top managers and professionals	0.211 <i>0.219</i>	0.073 <i>0.058</i>	0.832*** <i>0.304</i>	-0.206 <i>0.225</i>	-0.123 <i>0.382</i>	0.204 <i>0.135</i>
46 Mid-level professionals	0.563*** <i>0.196</i>	0.324** <i>0.156</i>	0.539** <i>0.260</i>	0.259 <i>0.203</i>	0.636** <i>0.306</i>	0.301* <i>0.178</i>
48 Foremen, Supervisors	-0.465 <i>0.583</i>	-0.134** <i>0.059</i>	-0.899 <i>1.084</i>	0.180 <i>0.639</i>	-0.011 <i>0.249</i>	-0.170*** <i>0.063</i>
54 Office workers	-0.511*** <i>0.194</i>	-0.163 <i>0.217</i>	-0.528 <i>0.341</i>	0.399 <i>0.348</i>	-0.874*** <i>0.306</i>	-0.175 <i>0.215</i>
62 Skilled industrial workers	-0.822** <i>0.347</i>	-0.163** <i>0.080</i>	-1.270*** <i>0.432</i>	0.256 <i>0.266</i>	0.015 <i>0.215</i>	-0.216*** <i>0.075</i>
63 Skilled manual laborers	0.601 <i>1.210</i>	-0.030 <i>0.203</i>	2.560** <i>1.078</i>	-2.670*** <i>0.831</i>	-2.910* <i>1.709</i>	0.099 <i>0.227</i>
64 Drivers	1.520*** <i>0.556</i>	0.254*** <i>0.087</i>	2.380*** <i>0.864</i>	-1.390* <i>0.739</i>	0.670 <i>0.863</i>	0.266*** <i>0.092</i>
67 Low skill industrial workers	1.133 <i>0.753</i>	0.035 <i>0.105</i>	1.540* <i>0.924</i>	-0.623 <i>0.495</i>	0.086 <i>0.340</i>	0.126 <i>0.074</i>

Standard errors italicized, \* = 90%, \*\* = 95%, \*\*\* = 99% statistical significance.

Table 16: Effects of trade on employment shares in nonmanufacturing firms

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

Standard errors italicized, \* = 90%, \*\* = 95%, \*\*\* = 99% statistical significance.

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 <i>0.223</i>	0.000 <i>0.011</i>	0.031 <i>0.307</i>	0.036 <i>0.044</i>	<b>0.413**</b> <i>0.185</i>	-0.002 <i>0.002</i>	0.333 <i>0.238</i>	-0.035 <i>0.055</i>
46 Mid-level professionals	0.187 <i>0.327</i>	-0.012 <i>0.061</i>	0.028 <i>0.418</i>	0.000 <i>0.066</i>	-0.068 <i>0.261</i>	-0.002 <i>0.062</i>	0.085 <i>0.354</i>	-0.040 <i>0.055</i>
48 Foremen, Supervisors	<b>0.485*</b> <i>0.286</i>	0.021 <i>0.025</i>	0.650 <i>0.417</i>	0.030 <i>0.026</i>	-0.053 <i>0.272</i>	-0.010 <i>0.034</i>	-0.117 <i>0.272</i>	-0.008 <i>0.038</i>
54 Office workers	-0.162 <i>0.307</i>	0.062 <i>0.041</i>	-0.231 <i>0.469</i>	0.025 <i>0.041</i>	0.103 <i>0.253</i>	-0.039 <i>0.075</i>	0.180 <i>0.367</i>	-0.008 <i>0.044</i>
62 Skilled industrial workers	<b>1.250*</b> <i>0.752</i>	-0.016 <i>0.031</i>	<b>1.530*</b> <i>0.835</i>	-0.002 <i>0.038</i>	<b>-1.013*</b> <i>0.546</i>	0.139 <i>0.097</i>	<b>-1.158*</b> <i>0.627</i>	0.153 <i>0.097</i>
63 Skilled manual laborers	<b>6.196**</b> <i>2.536</i>	0.064 <i>0.190</i>	<b>4.460**</b> <i>2.264</i>	0.132 <i>0.211</i>	<b>-3.435*</b> <i>1.795</i>	0.208 <i>0.234</i>	-2.687 <i>1.755</i>	0.273 <i>0.233</i>
64 Drivers	<b>0.941*</b> <i>0.546</i>	-0.054 <i>0.051</i>	0.606 <i>0.726</i>	-0.003 <i>0.060</i>	-0.317 <i>0.500</i>	<b>0.145**</b> <i>0.060</i>	-0.145 <i>0.624</i>	<b>0.139**</b> <i>0.069</i>
67 Low skill industrial workers	<b>-3.255*</b> <i>1.668</i>	-0.015 <i>0.053</i>	<b>-3.620**</b> <i>1.852</i>	-0.048 <i>0.068</i>	<b>2.106*</b> <i>1.186</i>	-0.178 <i>0.170</i>	<b>2.451*</b> <i>1.369</i>	-0.230 <i>0.174</i>

Standard errors italicized, \* = 90%, \*\* = 95%, \*\*\* = 99% statistical significance.