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That was then, this is now: Skills and Routinization in the 2000s

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Abstract: We analyze changes in the skill content of occupations in US four-digit manufacturing industries between 1999 and 2010. Following a 'task-based' approach, we elaborate a measure of Non-Routine skill intensity that captures the effects of industry exposure to both technology and international trade. The paper adds to previous literature by focusing on both the determinants of demand for Non-Routine skills and their effects on industry productivity and wages. The key finding is that import competition from low-wage countries has been a strong driver of demand for Non-Routine skills during the 2000s. Both technology and imports from low-wage countries are associated with mild cross-industry convergence in skill intensity while imports from high and medium wage countries are at root of persistent heterogeneity across occupational groups. We also find that higher Non-Routine skill intensity has had at best a modest effect on productivity and wages, except for high-skill occupations.

Keywords: Skills, Tasks, Routinization, Trade, Technology
JEL Codes: F16, J21, J23, O33

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1 Introduction

This paper elaborates an empirical study of changes in the skill content of occupations in US manufacturing industries over the 2000s. In the conceptual approach used here the intensity of use of a task is a direct measure of the demand for the skill needed to perform a specific work activity (Autor, Levy and Murnane, 2003; Levy and Murnane, 2004). Breaking down productive activities into functionally different task groups moves beyond traditional categorizations, such as high-skilled or low-skilled workers, and opens up new possibilities for understanding the process by which individual abilities emerge, combine, or are selected out as a result of innovation and structural change. This 'task-based approach' is an appealing conceptual framework for several reasons. To begin with, it allows for a more flexible interpretation of the relation between labor and capital in performing work tasks, and this is especially relevant in those contexts in which technology plays a dual role, partly complementing and partly substituting human work (Autor, 2013). Clearly this approach is grounded in an interdisciplinary view whose central tenet, traceable to Herbert Simon (see e.g. 1969), holds that machines perform better physical and cognitive 'routine' tasks that can be codified in the form of instructions while humans retain a cognitive comparative advantage at 'Non-Routine' activities that involve i.e. complex pattern recognition (Langlois, 2003). Yet another advantage of the task approach is that it accommodates empirical findings of non-neutral labor market outcomes due to the diffusion of new General Purpose Technologies (GPTs)[4] and associated changes in the organization of production for which the

[4] Note that the task-based model suits also other radical technological transitions, for example electrification in the IXX century (Gray, 2013).

traditional capital-skill complementarity hypothesis (i.e. Krusell et al. 2000) does not suffice.[5]

Building on the above framework, the goal of the paper is to analyze the determinants and the effects of changes in the demand of Non-Routine (NR henceforth) skills, a particular set of workers' abilities that are used when carrying out analytical and interactive tasks. We focus on the US manufacturing industry in the period 1999-2010, no doubt a turbulent and hence interesting time due to the co-occurrence of China's admission to the WTO and the great recession at the end of the decade. Previous studies on the determinants of skill content call attention to the role of Information and Communication Technologies (ICTs) and of trade. The seminal study by Autor, Levy and Murnane (2003) (ALM henceforth) first put forth the notion of 'routinization' to explain the empirical association between ICTs' diffusion and changes in the demand for workers' skills. In particular, ICT-driven routinization induces 'polarization' in employment and demand for skills, that is, higher decline of routine-intensive jobs, i.e. accountant, and wages relative to occupations that are either at the top or at the bottom of the earning distribution (Autor et al, 2008; Goos and Manning, 2007). This is because ICT capital substitutes for routine tasks, thus reducing the demand for routine-intensive occupations, while increasing the productivity of Non-Routine analytical and interactive skills and thus the demand for high skill professionals.[6] Interestingly, these empirical

[5] Within the economics literature on the effect of ICT technologies on the labor markets, early studies generally explain the increase in the skill premium using a demand-supply framework augmented for directed technical change (see, e.g., Krueger et al., 1993, Katz and Murphy, 1992; Autor et al, 1998; Goldin and Katz, 1998; Acemoglu, 1998). This approach, however, is unable to explain polarization and has hence been replaced by the more general routinization hypothesis discussed in the main text (see Autor, Katz and Kerney, 2008). The debate is well summarized in Acemoglu and Autor (2011).

[6] Among innovation scholars Nelson and Phelps (1966) and Freeman and Perez (1988) have acknowledged explicitly the heterogeneity of workers' skills and their role in the diffusion of technology.

regularities are common to most advanced economies and not just peculiar to the US labor market.[7]

Recent evidence suggests that the influence of ICTs may have waned away during the last decade. Weber and Kauffman (2011) observe that ICT-related investments in US manufacturing reached a plateau during the 2000s, and that the lion share of capital spending is now on maintenance activities rather than new technology acquisition. Likewise Aizcorbe et al (2006) call attention to a break in the technological trajectory of ICTs sometime in the early 2000s that is ascribed to a combination of changes in economies of scale and a shift in product mix.[8] This, while not necessarily implying reduced importance of technology, calls at least for a reconsideration of the one-to-one mapping between ICTs and NR skills. After all it seems plausible that, after take-off and growth, the trajectory of ICTs may have reached a stage of maturity and, as codification has caught up with the skills that pushed the technological frontier in the 1990s (Vona and Consoli, 2011), the dynamics of both productivity and wages have adapted accordingly. The first goal of the paper is to take stock of these phenomena, and to assess whether during the 2000s technological change has had a similar detrimental effect on routine skills, thus spurring divergence across occupations and across industries.

The debate on the changes in the skill content of the workforce has been recently enriched by closer consideration of the impact of trade. This is no doubt due to the unfettered expansion of China and the catching up on the part of various emerging

[7] See Spitz-Oener (2006); Goos et al (2009); Acemoglu and Autor (2011); and Jaimovich and Siu (2012).

[8] See also Oliner and Sichel (2000), Wolff (2002) and Basu and Fernald (2007). To illustrate, the product cycle for semiconductors (i.e. the lag between successive releases) shifted back to a 3-year period since 2000 (Jorgenson et al, 2008) after being reduced to 2 years during the intense competition of the mid-1990s. Recent examples of ICTs diversification also confirm this e.g. Hubbard (2003) and Athey and Stern (2002).

economies that has transformed the global import-export matrix (Hanson, 2012).[9] With regards to the US, the general agreement is that higher exposure to foreign competition had a negative employment effect, especially after China's entry in the WTO in 2001 (Pierce and Schott, 2012; Autor et al, 2013). The literature draws attention to two mechanisms. On the one hand the progressive fragmentation of supply chains (Baldwin, 2011) has opened up the scope for offshoring of routine tasks involving minimal complexity (Blinder, 2009). On the other hand domestic producers have reacted to foreign competition by switching to higher quality products and innovations requiring intensive use of Non-Routine tasks (Verhoogen, 2008; Guadalupe, 2007). On the whole this suggests, albeit indirectly, that trade has had a significant impact on the composition of the workforce and that this effect may have been heterogeneous across industries and occupations.[10] With the notable exception of Lu and Ng (2013), few have debated the following matter: what has been the impact of trade on the skill content of US occupations and industries during the large uptake of trade with low-wage and emerging countries? Addressing this issue is the second objective of this paper.

By tackling the two questions outlined above, this study adds to the existing literature in three ways. First, it focuses both on the determinants of the demand for NR skills and the effects of NR skills on performance, captured through changes in industry wages and productivity. Second, previous studies on the determinants of NR skills (Autor et al, 2003; Lu and Ng, 2013) arguably neglect the dynamic process by which the composition of the workforce gradually adapts to a new, ex-ante undetermined, target-level of NR

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[9] See e.g. Schott (2008); Puga and Trefler (2010) and Cadot et al (2011).

[10] Note that large trade shocks are not limited to the US: empirical evidence points to a direct, revealed effect of trade shocks on returns to skills in both developing (Verhoogen, 2008; Amiti and Davis, 2012) and developed countries (Guadalupe, 2007; Raitano and Vona, 2013). Bugamelli et al. (2010) show that the effect of the Euro and increased competition from China induced restructuring in the workforce composition, especially among low-tech sectors. See also Bloom and Van Reenen (2007) for firm-level evidence on the effects of changes in management practices.

skills. Our empirical strategy accounts for this by means of standard system-GMM techniques. Third, unlike past work our dependent variable is not the employment share of occupations ranked according to initial skill levels (see Autor et al. 2013) but, rather, a measure that combines in an unconstrained way both industry-level changes in NR skills *within* occupation and in the employment shares *between* occupations. We believe that this is an appropriate choice considering that large-scale technological revolutions induce composition effects on employment shares of occupations as well as changes in the skill content (Autor et al, 2003; see Vona and Consoli, 2011 for a life-cycle approach).

Our analysis yields three main findings. First and foremost, import competition from low-wage countries emerges as the main driver of demand for Non-Routine skills in the 2000s. Second, both technology and import from low-wage countries are associated with skill convergence across industries. This is consistent with literature showing that trade-induced adjustments are stronger in industries with lower initial skill levels (Bugamelli et al, 2010; Pierce and Schott, 2012). Furthermore, when allowing for heterogeneity across occupational groups we find that convergence of NR skill intensity across industries is not driven by convergence across occupations. Conversely, heterogeneity across occupational groups is persistent due to imports from high and medium wage countries. The last major finding is that upgrading Non-Routine skills has at best a modest effect on productivity and wages except for high-skill occupations.

The paper is structured as follows. Section two lays out the empirical strategy, followed by the description of the dataset in Section three. The central part of the paper deals with the analysis of the determinants of NR skills: section four presents the baseline model and unpacks heterogeneous effects on different occupational categories. In section five we focus on the effects of NR skills on wages of major occupational group and productivity. Conclusions summarize and sketch future research lines.

2 Empirical Strategy

This section describes our empirical strategy. To fix ideas, we are primarily interested in explaining Non-Routine skill intensity at time t in industry i (NRIit) as a linear function of trade and technology variables. In the second part of the paper we focus on an indicator of performance Y as function of NR intensity, trade and technology proxies. In formulae:

$$NRI_{it} = f(trade_{it}, tech_{it})$$

$$Y_{it} = f(trade_{it}, tech_{it}, NRI_{it})$$

The assumption of linearity of *f(.)* is not just for the sake of simplicity. The present paper is mainly an empirical study and relies on general theoretical arguments to derive testable predictions. Therefore, we do not put forth any theoretical justification to support the inclusion of interactions or nonlinear effects. In addition, the existing literature that investigate skill determinants using O-NET keeps the empirical specification as simple as possible to avoid misinterpretation of the effects of interest. Following on this we opted for not including other variables except our proxies of skills, trade or technology. To further corroborate this choice, we check if the financial crisis of 2007 has an effect on our variables of interest and find no significant differences. The same holds when we include proxies for industry demand.

In previous studies on skill determinants using O-NET (e.g. ALM, 2003; Lu and Ng, 2013) the identification of the effects of interest is warranted by the inclusion of unobservable individual effects and/or by the use of IV. An IV approach is particularly appealing here because unobservable time-varying factors likely affect both the demand for NR skills and the evolution of technology. However, previous work has been unsuccessful in finding appropriate instruments both for trade and technology proxies. By way of example, Autor and Dorn (2013) and Autor, Dorn and Hanson (2013) use the level of NR skills in the 1950s as instrument for NR skill levels in later decades to explain changes in employment shares across occupational groups. As they admit, however, instruments based on initial conditions work well in explaining the demand for NR skills in the 1960s but gradually lose explanatory power for the following decades, hence becoming weak predictors of NR skills in the crucial decade of the ICT revolution.

An important, and yet neglected, source of bias is true state dependence in the data generating process. In our case the 0.97 point estimate of the autocorrelation coefficient for NR skills indicates that state dependence characterizes the adjustment in industry demand of NR skills.[11] Such a high degree of persistence is not surprising considering that both the demand and the supply of skills are variables that change slowly over time. For what concerns demand, this is so owing to non-negligible hiring and firing costs due to skill specificity, while in the case of supply there are significant lags in the adjustment through training and education. Note that in past work, e.g. ALM (2003), state dependency may be less severe because the time-unit is a decade or a 5-year period. In a more recent instance, Lu and Ng (2013) consider an industry-by-year panel and correctly conclude that their results do not change when dynamics if properly accounted for. However their point estimates of the effect of the lagged dependent variable range between 0.05 and 0.15, well-below that of our data.[12] Indeed it is not surprising that the inclusion, or not, of the lagged dependent variable yields considerable differences in the estimated effect (see section 4.1 and the appendix). Retrospectively, these differences validate the choice of including the lagged dependent variable in our estimating

[11] Similar results emerge when using standard tests for serial correlation and presence of unit roots. Results are available from the authors upon request.

[12] We find high persistence even when using measures of NR skills similar to that of Lu and Ng (2013). Note also that in this study differenced GMM (Arellano and Bond, 1991) is used instead of the more general system GMM (Blundell and Bond 1998), and this is likely to bias downward the autocorrelation coefficient. In relation to this, Hauk and Wacziarg (2009) carry out a Montecarlo experiment to show that the differenced GMM tends to considerably underestimate the autocorrelation coefficient as compared with a system GMM estimator.

equations. A similar argument applies to our measures of performance, i.e. indsutry wages and productivity, which also display high persistency with estimated autocorrelation coefficients above 0.9. Our specifications in eq. 1-2 hence become:

$$NRI_{i,t} = \rho NRI_{i,t-1} + \beta_1 tech_{i,t-1} + \beta_2 trade_{i,t-3} + \mu_i + \mu_t + \varepsilon_{i,t} \tag{1}$$

$$Y_{i,t-1} = \rho Y_{i,t-1} + \alpha_1 NRI_{i,t-1} + \alpha_2 tech_{i,t-1} + \alpha_3 trade_{i,t-3} + \mu_i + \mu_t + \varepsilon_{i,t}, \tag{2}$$

where μ_i, μ_t and $\varepsilon_{i,t}$ are respectively a industry effect, a time effect and a generic disturbance term, independent across individuals. While it is well-known that under these circumstances OLS and Fixed effect estimators deliver biased estimates of both the autocorrelation and the effects of interest (Nickell, 1981), the debate as on what is the best fix is still open. The system-GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) has gained some consensus among applied economists. The general idea of dynamic GMM estimators is to instrument the lagged dependent variable with its lags or lagged differences. Within this class of estimators, the system-GMM reduces the small-sample bias of the differenced-GMM (Arellano and Bond, 1991) when the endogenous variables are persistent using moment conditions both for the equation in level and in first-differences (Bond 2002). This bias derives from the pure random disturbance generated when differencing a persistent variable. Clearly, such a random disturbance will be weakly correlated with any instrument, thereby reducing its power. Hauk and Wacziarg (2009) recently showed that in presence of large measurement errors a between-estimator (BE) reduces the bias in estimated coefficients as compared to a system-GMM estimator.[13] On the basis of this, we use a BE estimator to carry out a

[13] Comprehensive Montecarlo evidence provided in Hauk and Wacziarg (2009) shows that the measurement error bias and unobservable heterogeneity bias mutually offset each other when using simple between-estimator. In turn, as the measurement error increases, estimators that account for unobservable heterogeneity (such as FE or dynamic GMM) become less precise in estimating the parameters of interest. System GMM, however, remains relatively more robust than differenced-GMM and FE estimators.

robustness check by regressing the dependent variable at time *t* over itself at time *t-k* and a time-averaged explanatory over *t* and *t-k*.

The inclusion of the lagged dependent variables does not fully address the issue of endogeneity of trade and technology variables, even if the lagged dependent variable is a good proxy for industry-time-varying factors that are likely to bias our effects of interest. For what concerns technology, we exploit the long data series available for our technology proxy and use past values as proxies of current ones. For what concerns trade variables, we could have followed the same route but we would have incurred in the problem of having 'too many instruments' compared to the number of observations (Roodman 2009a). Including too many instruments would artificially improve the fitness of the first stage up to the point where the variables instrumented are perfectly predicted and hence equivalent to the variables non-instrumented. As a result we include our trade variables with a 3-year lag rather than instrumenting them, under the assumption that trade variables are predetermined. This also allows us increasing the number of observations for the estimates since trade variables are only available until 2007. Likewise since available data for technology are up to 2009, we lag our technology proxy. This peculiar, admittedly anomalous, lag structure is the best option for preserving an acceptable time span in the analysis of the 2000s, and for ensuring the inclusion of the recent economic recession.[14]

Further details of the empirical strategy are outlined in the section on the results. Let us now turn to illustrate our dataset and the measure used to track the evolution of NR skills.

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[14] Our results are robust to changes in the lag structure (not surprising since our explanatory variables are also highly persistent) and to changes in the number of instruments that depend on the number of lags.

3 Data and variables

Our empirical analysis combines data from three different sources. First, we retrieve Bureau of Labor Services (BLS) data for employment and hourly wages across industries (four-digit occupations based on the Standard Occupational Classification System – SOC henceforth) and four-digit NAICS. The latter is matched with information on occupation-specific task content, the O-NET abilities survey of the US Department of Labor. Lastly, we use the data from NBER for variables on International Trade Data, technology, productivity and remaining controls. Data construction and measurement are detailed below. Further details are provided in Appendix B.

3.1 Construction of task variables

The US Department of Labor's O-NET abilities survey is the main source of information to compute our task variables. This is a comprehensive database of worker attributes and job characteristics that replaced the Dictionary of Occupational Titles (DOT). Data collection is implemented by means of questionnaires aimed at both job incumbents and occupational analysts.15 To keep up with changes in the US labor market O-NET data are regularly updated and adapted. These revisions entail two sources of variation in terms of task content: (i) occupations are added, reclassified or eliminated in accordance with periodical revisions of the SOC structure; (ii) scores of worker characteristics increase or decrease as a result of changed importance. In this paper we kept track of all revisions over the period 2002-2010 and created a unique dataset of 855 four-digit SOC occupations. Being US employment data classified according to the SOC system, O-NET information on job content can be matched with other data sources, in particular industry-

[15] For further information on data collection as well as critical issues of O-NET, see the comprehensive book by Tippins and Hilton (2010).

occupation total employment from BLS for the period 1999-2010.16 Since the first usable wave of O-NET is for 2002 we miss information on employee abilities in the period 1999-2001. To cope with this, we assign to period 1999-2001 time invariant information drawn from the 2002 wave of O-NET. Using crosswalks across different datasets, we obtain a quite balanced industry-by-year panel dataset including 86 manufacturing industries for the period 1999-2010.17

The central idea of the 'task approach' is that a job generates output by carrying out multiple activities, and that occupation-specific tasks provide a measure of the skills that workers are expected to possess to perform the job (Autor, 2013). Considering the richness of its content and the breadth of the information contained in it, O-NET is therefore a powerful tool to operationalize this approach. The key dimensions for our variables of interest are job-specific characteristics such as e.g. communicating with others (NR Interactive), interpreting meaning of information (NR Cognitive), performing administrative activities (Routine Cognitive), performing physical activities (Routine Manual) – further details in Appendix B3. Accordingly, the scores assigned from the survey's respondents generate vectors of basic tasks that are specific to each SOC occupation. While such basic tasks are common to most jobs, a particular combination of scores in the use of each task distinguishes occupations from one another.

Following the seminal paper by Autor, Levy and Murnane (2003), our task constructs are built from a detailed examination of O-NET Work Activities and Work Context, i.e. the

[16] BLS data on employment for the period 1999-2010 encompasses different industry classification schemes: the 1987 Standard Industrial Classification (SIC1987), used until 2001, the 2002 North American Industry Classification System (NAICS), used until 2006, the 2007 North American Industry Classification System (NAICS), used thereafter. To cope with this, we developed a concordance table. See further details in Section B1 of the appendix B.

[17] Due to the different industry schemes, over the period 1999-2001 information is missing for the following four-digit 2007 NAICS industries: Other Food (3119); Apparel Accessories and Other Apparel (3159); Sawmills and Wood Preservation (3211); Lime and Gypsum Product (3274); Iron and Steel Mills and Ferroalloy (3311); Cutlery and Handtool (3322); Motor Vehicle (3361); Other Furniture Related Product (3379). Table 1 and Appendix B contain all the relevant information about missing values.

scores in basic tasks. These items are subsequently grouped together in four main categories: Non-Routine Cognitive (NRC), Non-Routine Interactive (NRI), Routine Cognitive (RC) and Routine Manual (RM). Table B1 in the appendix lists the 40 O-NET variables used in this study. The main task categories are computed by summing the score of importance for a particular SOC occupation. The index of task intensity is as follows:

$$NR\ Intensity_{it} = \sum_j Emp\ Sh_{ijt} * \left[\frac{NRC + NRI}{RM + RC}\right]_{ijt},$$

where NRC, NRI, RM and RC are the task constructs outlined above for industry *i* and occupation *j* in year *t*. $Emp\ Sh_{ijt}$ refers to employment share in industry *i* and occupation *j* in year *t*, constructed using data at the four-digit NAICS and four-digit SOC from BLS. It is worth stressing here that while the logic underpinning our task constructs relates to previous works, in particular ALM (2003), Acemoglu and Autor (2011) and Goos et al. (2011), our chosen measure is not the employment share of occupations ranked according to initial levels of Non-Routine skill content (see Autor et al. 2013) but, rather, an industry-level measure of Non-Routine skills. We believe that this construct captures both changes in the employment shares *between* occupations and changes in Non-Routine skills *within* occupation. This feature distinguishes the present paper from previous work based solely on within variation in task constructs due to changes in the composition of employment (e.g. Autor et al., 2003; Autor et al., 2013).[18]

Furthermore, to capture heterogeneity in the effect of our variables of interest across occupations we follow Autor and Dorn (2013) and differentiate between three broad

[18] We carried out several robustness checks by defining different measures of task content at the industry level. Our results are robust to the different definitions of our task variable. See Appendix B for further details.

occupational groups.[19] The first includes managerial, professional and technical occupations which are intensive in Non-Routine tasks (NRI and NRC) such as abstract thinking, ability to analyze and organize as well as interpersonal capacity. Occupations that belong to this group are categorized as high skill occupations (HS henceforth). The second occupational category encompasses routine-task intensive activities such as clerical and administrative support, and sales. These are medium skill occupations (MS henceforth). The last group features low-skill jobs such as mechanics, craft and repair occupations, and service occupations. These occupations are low skill occupations (LS henceforth). Similar to what was done for the task measure above, we build three different task measures referring to the three broad occupational categories: high skill (*NR intensity HS*), medium skill (*NR intensity MS*) and low skill (*NR intensity LS*).[20]

3.2 Labor Productivity and Hourly Wage measures

We analyze the effects of changes in Non-Routine tasks by focusing on labor productivity and hourly wages. The former is an aggregate (industry-level) measure of performance while the latter varies across occupations and thus provides useful insights on the impact of our variable of interest, NR intensity, over different types of workers. The labor productivity measure ($Prod_{it}$) is computed as value added per worker at the four-digit NAICS. This is the total value added in $ million per 1000 employees and is available on a yearly basis for the period 1989-2009. We opted for this measure because it captures the joint influence of changes in capital, as well as technical, organizational and efficiency change within and between firms (Bartelsman and Doms, 2000). Information on total value added and employment is extracted from the NBER-CES

[19] Table B2 in the appendix B presents the occupations classified in each broad occupational group.

[20] All task measures are aggregated at the occupational group by weighting for employment shares of each occupation belonging to the group.

manufacturing industry database (Becker and Gray, 2013). The source of the other performance indicator, average hourly wage for four-digit occupations, is BLS. Following the same logic underlying the construction of the task measures, we seek to capture heterogeneity across the three occupational categories by considering group-specific hourly wages, namely *Wage HS*, *Wage MS* and *Wage LS*.[21]

3.3 Measures of technology and trade

Throughout this study we proxy investments in ICT by using information on investment in capital equipment per worker available from the NBER-CES Manufacturing Industry database (Becker and Gray, 2013). This is an admittedly crude measure due in part to data availability. At the same time, we believe that this simple measure is appropriate for our purposes considering the vast literature on the pervasiveness of automated processes in production technology (e.g. David, 2001; David and Wright, 2003; Brynjolfsson and McAfee, 2011) and their capacity to capture embodied technical change (Cummins and Violante, 2002).

We measure exposure to trade through an index of import penetration that are widely used in the literature (Bernard et al., 2006; Cunat and Guadalupe, 2009; Lu and Ng, 2013). Import penetration ratios are a reliable measure of the evolution in exposure of manufacturing industries to foreign competition. Accordingly, we define two measures of import penetration. *Imp Pen Hi-Med*$_{it}$ is the ratio of the total value of US imports from high and medium wage countries over the total value of shipments and imports minus exports. To capture effects coming from low-wage countries, we also define import

[21] Similarly to what has been done with task measures, we aggregate hourly wage at the occupational group level by weighting for employment shares.

penetration from low wage countries (*Imp Pen Low)* and for China (*Imp Pen China*).[22] To construct our measures, we employ U.S. import and export data of the manufacturing industries for the period 1996-2007 compiled by Peter Schott, and data on value of shipments from the NBER-CES manufacturing industry database.

Figure 1 shows the prolonged contraction in US manufacturing employment with two sharp accelerations coinciding with the recessionary phases of 1999-2003 and 2007-2010. Note that on both occasions the contraction has been relatively stronger for Medium- and Low-Skill occupations relative to High-Skill occupations.

[Figure 1 ABOUT HERE]

Table 1 presents the basic statistics for the variables in the regression analysis. For each variable we also include in the table the reference period and the source of data from which relevant information has been drawn. Figure 2 offers preliminary insights into the relation between the relative demand for skilled labor and our main explanatory variables, namely capital equipment and import penetration, over time. We observe, first, that the growth of NR intensity goes flat in coincidence with the two recessionary periods (gray lines)[23] and, second and more crucially for the remainder of the analysis, that import penetration from low wage countries accelerates faster than import from high- and middle-income countries especially after 2001[cf. quadrant (b) and (c)]. Incidentally, this pattern is very much driven by trade with China [quadrant (d)]. In turn, the growth of Capital reaches a plateau between 2004 and 2007 [quadrant (a)].

[Figure 2 ABOUT HERE]

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[22] Low wage countries are defined as those countries with a GDP per capita less than 5% of US per GDP per capita.

[23] It is worth stressing how the relatively flat dynamics of our measure of Non-Routine task intensity in the period 1999-2001 should be linked to the construction of our measure for this time period. In particular, it is important to recall that we lack one source of within variation due to change in employee abilities within each occupation as the first usable wave of O-NET survey is for 2002.

Next, we present the correlation between these variables for two different groups of NAICS industries. Table 2a brings together four-digit NAICS industries with the lowest value of Non-Routine skill intensity which, unsurprisingly, are mostly low-tech industries such as footwear manufacturing; animal slaughtering and processing; and cut and sew apparel manufacturing. Conversely, Table 2b contains NAICS industries with the highest value of Non-Routine skill intensity, namely Computer and peripheral equipment manufacturing, navigational measuring, electro-medical and control instruments manufacturing and communications equipment manufacturing. This assortment is broadly consistent with various taxonomic exercises elaborated in previous studies (e.g. Castellacci, 2007 and 2008; or Malerba and Montobbio, 2003). Table 2c reports the correlation among *NR Intensity, Cap Equip*, *Imp Pen Hi-Med* and *Imp Pen Low* for the two groups of industries and difference tests among the correlation coefficients. The results show a positive and significant association between the relative importance of Non-Routine skill requirements, investment in capital equipment and import competition from low wage countries in industries with the lowest Non-Routine skill content. The correlation between Non-Routine skill intensity and import competition from low wage countries is also positive in industries with the highest NR skill content, but considerably lower than in industries with the lowest NR skills. Although not statistically significant from the coefficient in industries with the lowest non routine skill content (see column 3, Table 2(c)). This provides preliminary evidence of skill convergence across industries driven by import competition. Indeed, a graphical inspection (Figure 3) shows that skill growth in the period under analysis has been faster for industries with lower initial NR intensity.

[Table 1 ABOUT HERE]

[Table 2 ABOUT HERE]

[Figure 3 ABOUT HERE]

Let us now turn to the analysis of the determinants and the effects of changes in the demand for Non-Routine skills.

4 Determinants of Non-Routine Skills

This section presents the analysis for the demand of NR skills at indsutry level. Table 3 shows the baseline results. These are extended in Table 4 by allowing for heterogeneity across different occupational groups. To ease the interpretation, recall that our measure of NR skills is basically tantamount to a general measure of quality of employment.

4.1 Baseline specification

Table 3 shows a series of specifications progressively enriched by various controls. The common covariates are the lagged dependent variable, lagged capital equipment, our chosen proxy for ICTs, Cap Equip, and two time-invariant dummies for low- and medium-tech industries (Low Tech and Med Tech respectively).24 Both lagged capital equipment and the lagged dependent variable are instrumented: the former with the second lag, the latter with lags from 2 to 5. Four preliminary observations are in order. First, standard tests validate our specification: the Hansen test does not reject the null hypothesis of instruments' exogeneity and the p-value is generally close to the minimum threshold of 0.25 suggested by Roodman (2009b) for dynamic GMM, while the Arellano-Bond tests always fails to reject the alternative hypothesis of second-order

[24] We define three dummies to control for the effect of the technological content of different industry aggregations. The dummies are defined distinguishing between low (*Low Tech*), medium (*Med Tech*) and high (*High Tech*) technology sectors in manufacturing (according to the classification of Eurostat). Table B3 in the Appendix presents the distribution of NAICS2007 four-digit codes across the three different groups.

autocorrelation.25 The validity of the standard specification tests applies to all the models presented in the remainder of the paper. Second, results are clearly affected by the use of a dynamic specification. This is evident from a comparison between Table 1 and Table A1 in the appendix where the main specifications (Model 1 and 3) are estimated using OLS and FE without the lagged dependent variable. This leads us to conclude that a dynamic specification reduces the bias of the estimated effects, especially for capital equipment. Third, the effects of the lagged dependent variable $\hat{\rho}$ (well above 0.9) and of the two dummies Med Tech and Low Tech (negative relative to the reference category High Tech) point to high persistence in the process of adaptation in NR skill intensity . As a final remark, for sake of clarity, we comment on the coefficient of the explanatory variables without repeating that they are lagged.

Model 1 uses only Cap Equip as external explanatory variable. This is akin to the specification of the classic ALM (2003) paper, with the exception of the lagged dependent variable. The point estimate is positive but not statistically different from zero (p-value=0.269) to indicate that the aggregate effect of ICTs adoption on Non-Routine skills weakened over the last decade. The specification of Model 2 includes trade with high- and medium-wage countries and is equivalent to the model used by Lu and Ng (2013) augmented with the lagged dependent variable. Our results corroborate their finding of a positive and significant effect of import penetration on the skill quality of the workforce over the period 1999-2010. In Model 3, our favorite specification, the effect of trade is decomposed by considering import penetration from low wage countries. Unlike Lu and Ng (2013) we find that the positive and significant effect of trade with high- and medium-wage countries is now totally absorbed by Imp Pen Low. This resonates with the

[25]The differenced Sargan test (not shown here) generally confirms that system GMM is the appropriate specification compared to differenced GMM.

earlier remarks about Figure 3. Notice also that the growth of NR intensity goes flat in coincidence of the two recessionary periods (cf. Figure 2). Table A2 in the appendix shows that our main results of Model 3 are confirmed when using a robust BE estimator (Hauk and Wacziarg, 2009).

The inclusion of Imp Pen Low yields a twofold increase of the coefficient of capital equipment, which is now statistically significant at 95% level. Although the correlation between Imp Pen Low and Cap Equip is rather modest -0.17, it is likely that industries with higher exposure to trade from low-wage countries adjust not only their labor force skills but, also, the use of complementary inputs like capital equipment. Model 3a and 3b deal with this issue by re-estimating Model 3 split respectively for industries below and above the pre-sample median of the initial level of Imp Pen Low, computed for 1989-1995. The results are striking: while the point estimate of Imp Pen Low (resp. Cap Equip) is statistically significant (resp. insignificant) only in industries with highly exposed to competition of developing countries, the opposite holds for Cap Equip (resp. Imp Pen Low). Interestingly, the coefficient of Cap Equip is much higher in industries with high exposure to Imp Pen Low, but displays a high variability that makes it statistically insignificant. This is broadly consistent with the finding of Autor, Dorn and Hanson (2013) that the effects of trade from low wage countries and of technology do not overlap. From this we conclude that differences in the effect of technology across industries may not be visible unless import from low wage countries is accounted for.

The statistical significance of the estimated effects may not correspond to economic significance. This is not the case here since the size of the two short-run effects of Cap Equip and Imp Pen Low reflects the increasing importance of the latter relative to the former. In particular, a one standard deviation increase in Cap Equip (resp. Imp Pen

Low) explains 2% (resp. 3.8%) of a standard deviation in NR intensity.26 Note that the long-term effects of these two variables are considerably larger, i.e. more than 11 times, than short-term effects.27

[Table 3 ABOUT HERE]

The descriptive analysis of in Figure 2 may suggest a mild tendency towards industry catching-up in the level of NR skills. However, high values of the autocorrelation coefficient for NR intensity together with negative and statistically significant coefficients of the dummies Low Tech and Med Tech in Table 3 point to considerable persistence in the demand for NR skills. We investigate this by splitting the sample using the median of the initial level of NR skill intensity and excluding the Low Tech and Med Tech dummies. Models 3c and 3d illustrate that Imp Pen Low and Cap Equip have a large and statistically significant effect only in industries with a below-median initial skill level. In turn, the positive and near significant (p-value=0.120) effect of Imp Pen Hi-Med in skilled industries is offset by a negative and significant effect in unskilled industries. In sum, at industry level, trade from low-wage countries and Cap Equip emerges as the strongest convergence force for NR skills, while trade with high wage countries is a clear source of divergence.

In sum, three major findings stand out so far. First, as would be expected from the descriptive evidence of Table 2, Imp Pen Low induces restructuring and skill adaptation especially in low-skill industries that are arguably more exposed to competition from low wage countries. The fact that the adjustment to foreign competition depends on the initial

[26] A possible objection is that the effect of *Imp Pen Low* is reduced by the particular lag structure chosen (see section 2). To check, we replicate the analysis using a shorter lag structure and find that both the size and the statistical significance of the estimated coefficients is fully consistent with those of Model 3. Results are available upon request.

[27] The long-run effect is equal to the short run effect multiplied by $\frac{1}{(1-\hat{\rho})}$ where $\hat{\rho}$ is the estimated auto-correlation coefficient.

skill level and is a source of skill convergence across industries is in line with previous studies on both European countries (Bugamelli et al, 2010) and the US (Pierce and Schott, 2012). Second, technology, proxied by capital equipment, is not a source of skill divergence but, rather, of mild cross-industry convergence. This suggests that as ICTs have matured and activities to them associated have been codified, the impact of technology may have faded away (Vona and Consoli, 2011). Third, import from high- and medium-wage countries is the main source of cross-industry skill divergence, probably owing to the fact that trade between high and medium-income countries is mostly intra-industry and hence exhibits strongly persistent industry-specific patterns.

4.2 Heterogeneity in occupational skill content

Models 1-3 in Table 4 replicate the analysis of Table 3 by allowing for heterogeneity across the three occupational categories defined earlier. As expected from employment patterns depicted in Figure 1, the results reveal substantial heterogeneity across occupational groups. First, skill persistence, captured by the lagged NR occupation specific coefficient is stronger for supervised occupations, viz. LS- and MS-, relative to HS occupations. With regards to our main explanatory variables, Imp Pen Hi-Med has a negative and significant effect on LS but a positive effect on the other occupations. Taking into account significance levels, and considering the results for above-median split sample of Table 3, we conclude that Imp Pen Hi-Med is a source of skill divergence mainly between middle and low occupations. Second, in accord with ALM (2003) Cap Equip continues to exert a polarizing effect since skill upgrading is stronger for high and low occupations compared to middle occupations. Third, Imp Pen Low is also a source of significant skill polarization. This result, in line with the Heckscher-Ohlin model, suggests that trade is a source of inequality in the use of certain inputs or tasks, in this case Non-Routine tasks, especially between countries with very large differences in endowments. For what concerns low skills the net effect depends on the direction of the adjustments that follow trade-induced job loss (see also Figure 3).28 On the whole, the share of low-skilled occupations will be lower but the surviving workers will be more qualified.

[Table 4 ABOUT HERE]

Models 4-6 in Table 4 further articulate the effect of trade by breaking down Imp Pen Low into two import penetration ratios, thus isolating imports from China (Imp Pen China) from those of other low-income countries (Imp Pen Low No China). Imp Pen China has a negative but not significant impact on low-skill occupations and a positive effect on the remaining groups, especially high-skilled for which the effect is also statistically significant. The coefficient for the HS category is in line with earlier remarks on the fragmentation of production chains (Baldwin, 2011) and the comparative advantage that countries like China have gained in labor-intensive sub-activities within high-tech industries (Krugman, 2008; Hanson, 2010). In addition the demand of NR skills is expected to increase especially among hi-skill occupations as a result of jobs intensive in routine tasks being offshored to low-wage countries. The positive effect of Imp Pen Low on the NR skills among lower occupations is fully captured by the effect of other low-wage countries except China. This finding is consistent with recent evidence on the shift from low- to middle skill-production in China (Amiti and Freund, 2010). By analogy, the selection effect on the quality of the workforce in low-skill occupations

[28] For the sake of space, we do not report results for employment. However, consistently with the literature, *Imp Pen Low* has a negative, large and significant effect on employment of low-skill workers. A recent study by Autor, Dorn, Hanson and Song (2013) finds that workers initially employed in industries with higher exposure to Chinese competition are more likely to change job and to move out of manufacturing altogether, high-wage workers are able to relocate before large-scale restructuring occur and, thus, to avoid significant earning losses, while low-wage workers, generally less mobile, are more likely to either be laid off.

should be stronger for low-wage countries that remain specialized in low-skill production.

Note that our results are qualitatively confirmed by the use of the BE estimator (see Table A2 in the Appendix A). For the HS group, the effect of China and Cap Equip is smaller and loses statistical significance while import penetration from High- and Medium-income countries turns statistically significant. On the other hand, the impact of trade with China is negative and significant for LS occupations. Broadly speaking, this suggests that the effect of China on skill upgrading is not very robust, while Imp Pen Hi-Med is a stronger driver of divergence among occupational groups.

Our results also suggest substantial heterogeneity in the effect of trade and technology across occupational groups, but do not reveal whether these differences are statistically significant. To gain further insights we plot in

Figure **4** and Figure 5 the 95% confidence intervals for the estimated coefficients and interpret non-overlapping confidence intervals as indicating statistically significant differences.

Figure **4** shows the estimated coefficients and 95% confidence intervals for specifications 1 through 3 of Table 4: the only significant difference is between lower and middle occupations for Imp Pen Hi-Med. Figure 5 reports coefficients and 95% confidence intervals for model specifications 4 through 6 of Table 4: here significant differences are found between low and middle occupations for both import penetration from high and low wage countries. On the whole, this corroborates our results on the role of Imp Pen Hi-Med as a source of skill inequality between low and middle skill occupations, while Imp Pen Low has an opposite equalizing effect.

5 Effects of NR skills

This section will propose an analysis of the effects of NR skills in terms of performance at industry level divided in two parts. The first focuses on productivity, the second on wages.

5.1 Productivity

Table 5 shows results for the analysis of productivity growth measured as value added per worker. To take into account the dynamic nature of the process, our estimations are based on system GMM.29 In particular we use a catching-up equation (e.g. Griffith et al, 2004) in which the dynamic term is the lagged distance-to-frontier effect computed as the difference between the productivity of each industry and that of the most productive industry divided by the productivity of the latter (Distance to frontier).30 The inclusion of the distance-to-frontier term allows modeling productivity dynamics as dependent on the scope of catching up of the specific industry at stake (Nicoletti and Scarpetta, 2003). All variables are in log to allow direct interpretation of the effects in terms of elasticity.

[Table 5 ABOUT HERE]

The first specification, Model 1, shows that the effect of skills is, as expected, positive and statistically significant, and that a 1% increase in the intensity of NR intensity yields a 0.2% increase in productivity. Note that this is similar to a short-term effect since it is obtained by controlling for distance-to-frontier term. The coefficient for distance-to-the-frontier suggests cross-industry convergence with a large effect of 7% catching-up on a yearly basis. Our catching-up specification of productivity dynamics allows us to capture

29 As in the case of skills above, standard statistical tests corroborate the validity of our choice and not need to be commented here.

[30] We use information from our productivity measure and define the productivity distance in sector *i* and year *t* as $\frac{Max\ (Prod)_t - Prod_{it}}{Max\ (Prod_t)} * 100$ where *Max(Prod)*$_t$ is the value of the most productive industry in year *t*

faster productivity growth in industries with lower initial level, as the positive sign of the dummies for middle- and low-tech industries confirms. However, this specification suffers from an omitted variable bias as many other sources of productivity growth are not included. We address this shortcoming by including various proxies for skills and other drivers of productivity.

The addition of industry employment shares of HS and MS, using LS as 'reference group', to Model 2 reverses the result for NR intensity, which is now negative. In turn, higher shares of HS and MS workers are observed to have positive productivity effects with short-term elasticity respectively of 0.15% and 0.1%. This suggests that the relative quantity of high-skilled workers matters more than the relative quality of the workforce for industry productivity growth.

To shed further light on the catching up we split the sample in two groups depending on the initial level of productivity, respectively above (Model 2a) and below (Model 2b) median productivity for the pre-sample period 1990-1998. Observe that the catching-up is concentrated in industries above median productivity level. Since the distribution of value added per capita is right-skewed, industries with average productivity level catch up with those at the frontier. For what concerns the effect of skills, the only difference is the larger impact of HS and MS in low-productivity industries. This suggests that skill catching up is accompanied by a productivity catching up in industries with low initial productivity levels.

The next step consists in including other productivity-drivers selected on the basis of previous studies. The specification in Model 3 includes Cap Equip and the usual proxies of international competition. Both sets of variables are expected to positively affect productivity growth. The former effect derives straightforwardly from any endogenous growth models while the latter depends on firm selection in new trade models à la Melitz

(2003). We observe that, first, the effect of NR intensity is again negative and near significant (p-value=0.141) while the elasticities associated with Emp Sh HS and Emp Sh MS increase above 0.2. Secondly, the coefficient Cap Equip is, as expected, positive and statistically significant with a modest short-term elasticity of 0.01. Third, the two measures of import penetration have no particular influence on productivity. But, if any, the influence of trade tends to be negative.

Let us reflect on how our results compare with the existing literature. For what concerns technology, we confirm previous findings on the positive impact of ICTs on industry productivity (Siegel and Griliches, 1992; Jorgenson et al, 2008). For what concerns trade, the effect is not in line with new trade models à la Melitz (2003). It is also appropriate to remark that results for trade are not always robust. To illustrate, using a BE estimator, see Appendix A (Table A3) the effect of Imp Pen Low is positive and significant while the opposite holds for Imp Pen Hi-Med. Another difference in the BE estimator concerns the much larger effect of Emp Sh HS relative to Emp Sh MS. Finally, our finding on the effect of NR skills are consistent with a study by Wolff (2002) showing that growth in cognitive skills has a positive, albeit modest, association with industry productivity growth. Reassuringly, this main result on the effect of NR skills on productivity is robust to changes in specification and to different productivity measures.31

5.2 Industry Wages

Change in wages is frequently used in the study of the dynamics of skills and employment. The existing literature analyzes extensively on the effect of routinization and trade on wage inequality, i.e. the wage difference between higher and lower

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[31] In particular, it is robust using a classic dynamic specification rather than a catching-up one, a BE estimator (Table A2 in Appendix A) and different measure of productivity growth (TFP and output per worker). In general, the effect of *NR intensity* and *Emp sh HS* on productivity seems slightly higher in these cases, but we prefer the catching up specification as it allows to link skill and productivity catching up.

occupations. The usual assumption is to rank occupations according to their initial skill levels, so that the effect of interest is not skill upgrading on wages but rather trade and technology on wage mediated by the initial skill level. In this section we address a complementary research question: how much do wages react to upgrading in the NR skill content of an occupation?32 Wages are used here as a measure of economic performance at occupational level. This shift in perspective is possible since our dataset allows building skill measures for occupational macro-groups that vary over-time and across industries.33 All else equal we expect that workers with higher NR intensity be paid more. Arguably this fits well with institutional features of the US labor market, in particular decentralized bargaining and flexible wage setting.

The evolution of wages of occupation i in industry j is characterized by true state dependency which leads us to adopt, for the same reasons discussed earlier with regards to NR intensity, a dynamic specification. On the other hand, however, the lagged dependent variable is not normally included in the standard Mincerian wage equation. Hence, in Table 5 we compare two main specifications for wages: the baseline model with industry fixed effects, but without dynamics (Models 1-3), and our favorite dynamic specification, estimated with system GMM (Models 4-6). Here we instrument the lagged dependent variable, occupational-specific level of NR intensity and its share of employment. Again, all variables are in log to interpret the effects in terms of elasticity.

The specifications of Model 1-3 in Table 5 show that the effect of NR intensity is positive and statistically significant across all the occupational groups. However, the

[32] This shift in perspective seeks to fill two gaps in the literature. First, the industry dimension is often neglected in the existing literature. Second, we focus on the effect of a time-varying measure of skill. To reiterate, the skill content within-occupation changes substantially over time in response to changes in trade and technology and these changes should affect wages.

[33] Recall from section 2 on data that also the skill intensity of each macro occupation varies across sectors as the employment shares of each elementary SOC occupation vary by sector. Note that macro-occupations are an aggregate of elementary SOC occupations.

estimated elasticity is decreasing in the occupational ranking, and is significantly lower for LS occupations. Also, Emp HS has a positive wage effect for clerks (p-value=0.114) and even more so for lower occupations. Conversely, Emp MS is associated with a statistically significant wage penalty for all occupational groups. The effect of Cap Equip is not in line with our previous findings on skill demand: equipment magnifies the wage gap between HS and MS occupations relative to LS. The effect of trade is statistically insignificant for HS and MS occupations, while it is negative for LS ones where the coefficient of Imp Pen Hi-Med is also statistically significant.

[Table 5 ABOUT HERE]

Models 4-6 in Table 5 present our favorite dynamic specification. The first noticeable difference with the static model is that the effect of NR intensity remains statistically different from zero only for HS occupations. The effect is also quite large with elasticity equal to 0.44 in the short-term and 2 in the long-term. The coefficient associated with the employment share of HS is now positive and significant only for HS and MS, while that of LS disappears. In general, the effects of Non-Routine skills on wages appear to increase with occupational quality. Similar to what was observed for the determinants of NR intensity, wage persistence is instead decreasing in occupational quality.

Compared to Models 1-3 the new specifications yield clearer results for the remaining explanatory variables. Cap Equip has a positive wage effect on all occupations. While the short-run elasticity seems only slightly higher for LS occupations, the long-term effect is much higher: 0.13 compared to 0.04 for HS and MS occupations. Trade with high- and medium-wage countries is associated with a higher wage premium for high-skill occupations, consistent with our findings for NR intensity. The effect is modest but not small with a long-term elasticity of 0.23. Finally, Imp Pen Low has a near significant (p-value=0.118) negative effect only on low-skilled workers, which sum up to a long-term elasticity of 0.34. However, similar to what we remarked with regards to productivity, the effects of trade on wages are not very robust to the use of the BE estimator, while the other variables remain qualitatively unaffected (Table A3 in Appendix A).

The modest and unclear wage effect of trade is accounted by two effects that tend to cancel out at the macro-level. On the one hand a contraction in employment entails a selection effect that favors the survival of the best workers and increases their average productivity. On the other hand lower bargaining power compresses the wages of continuing workers. By and large, these findings are in line with other industry-level studies showing that trade competition has had little impact on US manufacturing wages (Edwards and Lawrence, 2010; Ebenstein et al., 2013).

6 Concluding remarks and future research

This paper has elaborated an empirical analysis of changes in the skill content of occupations in US manufacturing industries over the period 1999-2010. Following the seminal work of Autor, Levy and Murnane (2003) we adopt a task-based approach to analyze the determinants and the effects of changes in the demand of Non-Routine skills. Previous literature had highlighted the role of this particular set of workers' skills in relation to the diffusion of ICTs, and showed that technology augments the productivity of high skill occupations with strong interactive and analytical content while substituting for middle skill occupations with higher intensity of routine tasks. Such a process, it was observed, triggered significant divergence within and between occupations and industries during the 1990s. Against this backdrop the first goal of the paper was to assess whether technological change has continued to be a source of divergence throughout the 2000s. In the period under analysis, however, other forces have acquired prominence, in particular the rapid expansion of China and the catching up on the part of various emerging economies, with remarkable effects on the global import-export matrix. Accordingly, the second goal of the paper was to gauge the impact of trade on the skill content of US occupations and industries after the uptake of trade with low-wage and emerging countries.

Our analysis yields three main results. First, import competition from low-wage countries has induced skill adaptation in low-skill industries that are arguably more exposed to foreign competition. In general, trade emerges as a stronger driver of demand for Non-Routine skills than technology through the 2000s. The second key finding is that both technology and import from low-wage countries have induced skill convergence across industries but not owing to convergence across occupations. Indeed, import penetration from low-wage countries induces stronger skill upgrading for high- and low-skill occupations, and therefore a polarization effect. The last result is in line with previous literature and confirms that higher Non-Routine skills have overall modest effects on both productivity and wages except for High-Skill occupations.

Looking ahead, we think of this study as a starting point for a promising strand of future research. We assign a prominent role to skill and employment dynamics, and operationalise them in a way that arguably few have endeavored so far in the area of innovation studies. At the same time to keep things simple, we opted for an admittedly uncomplicated portrayal of technology which can no doubt be further enriched. One interesting development would consist in exploring more in detail the notion, mentioned but not fully developed in the paper, that technology evolves and that different stages of the life-cycle influence significantly the relevance of know-how and skills required to use them (Vona and Consoli, 2011). Another promising departure from the present paper would be a deeper analysis of the origin of new educational programs. In a truly dynamic process, the short-run imbalances triggered by trade and technology on the demand for skills are expected to stimulate the creation of educational packages aimed at facilitating the diffusion of the new skills. In this spirit, our future research will focus on the evolution of formal education and training in response to changing demand for skills. In acknowledging the potential of these and other future avenues of research, we hope that the present paper has made a first step in the right direction.

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Tables and Figures

Table 1: Summary statistics for the pooled sample

Variable	Mean	SD	25th percentile	50th percentile	75th percentile	Min	Max	N. of Obs.	Reference period	Source
Dependent variables										
NR intensity	0.842	0.102	0.764	0.846	0.908	0.639	1.197	1008	1999-2010	O-NET
NR intensity HS	1.172	0.029	1.16	1.172	1.186	0.999	1.268	1008	1999-2010	O-NET
NR intensity MS	1.024	0.052	0.981	1.022	1.07	0.851	1.176	1008	1999-2010	O-NET
NR intensity LS	0.705	0.094	0.609	0.711	0.798	0.552	0.884	1004	1999-2010	O-NET
Wage HS	30.936	4.152	28.155	30.562	33.342	16.911	49.93	1008	1999-2010	O-NET
Wage MS	17.645	2.68	15.85	17.604	19.31	10.794	30.64	1008	1999-2010	O-NET
Wage LS	13.856	2.706	12.092	13.84	15.262	8.179	25.289	1001	1999-2010	O-NET
Value added per worker	133.686	127.871	76.203	101.298	139.392	40.919	1850.1	1032	1998-2009	NBER-CES
Main variables										
Cap Equip	0.081	0.097	0.032	0.059	0.082	0.007	0.816	1032	1998-2009	NBER-CES
Imp Pen Hi-Med	0.184	0.114	0.106	0.177	0.23	0.011	0.983	1007	1996-2007	Schott
Imp Pen Low	0.063	0.086	0.01	0.024	0.098	0	0.645	1007	1996-2007	Schott
Imp Pen China	0.046	0.057	0.007	0.02	0.071	0	0.601	1007	1996-2007	Schott
Imp Pen Low No China	0.017	0.041	0.001	0.003	0.01	0	0.22	1007	1996-2007	Schott
Controls										
Emp Sh HS	0.2	0.125	0.119	0.158	0.203	0.066	0.743	922	1998-2009	O-NET
Emp Sh MS	0.155	0.056	0.113	0.145	0.194	0.034	0.329	922	1998-2009	O-NET
Distance to frontier	91.389	7.775	90.742	93.567	94.738	0	97.507	1032	1998-2009	NBER-CES
High Tech	0.14	0.347	0	0	0	0	1	1032	1999-2010	Eurostat
Med Tech	0.195	0.396	0	0	0	0	1	1032	1999-2010	Eurostat
Low Tech	0.545	0.498	0	1	1	0	1	1032	1999-2010	Eurostat

Notes: All statistics are weighted by average employment share over the period 1999-2010. Non-routine skill intensity, wage and employment share variables have missing information for the period 1999-2001 pertaining to the following industries: Other Food (3119); Apparel Accessories and Other Apparel (3159); Sawmills and Wood Preservation (3211); Lime and Gypsum Product (3274); Iron and Steel Mills and Ferroalloy (3311); Cutlery and Handtool (3322); Motor Vehicle (3361); Other Furniture Related Product (3379). NR intensity LS and Wage LS have additional missing values: Railroad Rolling Stock (3365) in 2003 and Other Leather and Allied Product (3169) in the period 2008-2010. Information on Wage LS is also missing for Leather and Hide Tanning and Finishing (3161) in the period 2008-2010. Information for employment share variables is missing for the year 1998. Import penetration variables have missing values in the period 1996-2007for the following industries: Apparel Knitting Mills (3151); Coating, Engraving, Heat Treating, and Allied Activities (3328). For year 2007 we additionally miss information for Manufacturing and Reproducing Magnetic and Optical Media (3346)

Table 2: Four-digit NAICS industries with the lowest (a) and the highest (b) value of initial Non-Routine Skill intensity and correlation among relevant variables (c)

(a) NAICS 2007 4-digit codes	NR intensity	Description
3162	0.639	Footwear Manufacturing
3116	0.643	Animal Slaughtering and Processing
3152	0.656	Cut and Sew Apparel Manufacturing
3211	0.658	Sawmills and Wood Preservation
3151	0.669	Apparel Knitting Mills
3117	0.671	Seafood Product Preparation and Packaging
3131	0.679	Fiber, Yarn, and Thread Mills
3122	0.681	Tobacco Manufacturing
3141	0.682	Textile Furnishings Mills
3315	0.683	Foundries

(b) NAICS 2007 4-digit codes	NR intensity	Description
3341	1.035	Computer and Peripheral Equipment Manufacturing
3345	0.993	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing
3342	0.981	Communications Equipment Manufacturing
3364	0.932	Aerospace Product and Parts Manufacturing
3343	0.928	Audio and Video Equipment Manufacturing
3344	0.917	Semiconductor and Other Electronic Component Manufacturing
3254	0.916	Pharmaceutical and Medicine Manufacturing
3333	0.898	Commercial and Service Industry Machinery Manufacturing
3332	0.882	Industrial Machinery Manufacturing

(c)	***NR Intensity***		***Difference test***
	Top 10 NAICS	***Bottom 10 NAICS***	
Cap Equip	0.1719	0.2087*	0.270
Imp Pen Hi-Med	-0.1365	-0.0249	0.695
Imp Pen Low	0.2858*	0.4808*	1.422

* Significant at the 5% level

Table 3: Effects of Import Competition and Technology on Non-Routine Skill Intensity

Dependent Variable: NR Intensity

Model	[1]	[2]	[3]	[3a]	[3b]	[3c]	[3d]
NR Intensity -1	0.9056***	0.9021***	0.9109***	0.9497***	0.8856***	0.8917***	0.8932***
	[0.026]	[0.028]	[0.025]	[0.016]	[0.052]	[0.063]	[0.039]
Cap Equip -1	0.0125	0.014	0.0248**	0.0061*	0.0394	0.0278**	0.0046
	[0.011]	[0.012]	[0.011]	[0.004]	[0.048]	[0.011]	[0.009]
Imp Pen Hi-Med -3	-	0.0120*	-0.0053	-0.0065	-0.0008	-0.0237***	0.033
	-	[0.007]	[0.007]	[0.006]	[0.014]	[0.008]	[0.021]
Imp Pen Low -3	-	-	0.0397***	0.0077	0.0390***	0.0540***	0.044
	-	-	[0.008]	[0.046]	[0.010]	[0.009]	[0.035]
Med Tech	-0.0031	-0.0028	-0.0049*	-0.0029	-0.0061***	-	-
	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]	-	-
Low Tech	-0.0100***	-0.0096***	-0.0109***	-0.0051**	-0.0123***	-	-
	[0.003]	[0.003]	[0.003]	[0.002]	[0.003]	-	-
Observations	922	899	899	447	452	436	463
N. of groups	86	84	84	42	42	41	43
AR2	-0.0372	-0.0246	-0.0694	-0.7815	0.2232	-1.1736	1.6108
AR2 crit. prob.	0.9703	0.9804	0.9447	0.4345	0.8234	0.2406	0.1072
Hansen J	69.0734	68.4903	66.322	31.3845	33.2794	31.4837	35.2418
Hansen df	63	63	63	28	28	27	28
Hansen crit. prob.	0.2798	0.2965	0.3631	0.3003	0.2256	0.2517	0.1629
Instruments	78	79	80	45	45	42	43

Notes: System GMM with Windmeijer correction for standard errors. The dependent variable is Non-Routine Skill Intensity and is an index of industry-level Non-Routine task intensity computed as: (sum of industry Non-Routine cognitive and interactive task inputs)/(sum of routine and manual task inputs). Specifications [3a] and [3b] include the sample split between industries with respectively below and above- median value of import penetration from low wage countries in the pre-sample period 1989-1995. Specifications [3c] and [3d] include the sample split between industries with respectively below and above- median value of NR Intensity for the initial year 2002. Med Tech=Medium-Tech dummy; Low Tech=Low-Tech dummy. All regressions are weighted by average employment share over the period 1999-2010. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level. Coefficients for the regression constant and year effects are not reported for sake of simplicity.

Table 4: Effects of Import Competition and Technology on Non-Routine Skill Intensity in three occupational groups (High-Skill, Medium-Skill and Low-Skill)

Dependent Variable: NR intensity	HS	MS	LS	HS	MS	LS
Model	[1]	[2]	[3]	[4]	[5]	[6]
NR Intensity HS -1	0.8174***			0.8149***		
	[0.029]			[0.030]		
NR Intensity MS -1		0.9341***			0.9299***	
		[0.032]			[0.034]	
NR Intensity LS -1			0.9192***			0.9184***
			[0.012]			[0.011]
Cap Equip -1	0.0097*	0.0035	0.0091***	0.0093*	0.0035	0.0108***
	[0.005]	[0.003]	[0.003]	[0.005]	[0.003]	[0.003]
Imp Pen Hi-Med -3	0.0018	0.0062**	-0.0079**	0.0042	0.0077**	-0.022***
	[0.007]	[0.003]	[0.004]	[0.008]	[0.003]	[0.007]
Imp Pen Low -3	0.0416***	0.0023	0.0212**			
	[0.008]	[0.006]	[0.009]			
Imp Pen China -3				0.0484**	0.0089	-0.0004
				[0.019]	[0.013]	[0.010]
Imp Pen Low No China -3				0.027	-0.0112	0.0770***
				[0.026]	[0.013]	[0.015]
Med Tech	0.0001	-0.0003	-0.0002	0.0001	-0.0004	-0.0005
	[0.004]	[0.001]	[0.001]	[0.004]	[0.001]	[0.001]
Low Tech	-0.0018	-0.0010**	-0.0005	-0.0014	-0.0007	-0.0027*
	[0.003]	[0.000]	[0.001]	[0.003]	[0.001]	[0.001]
Observations	899	899	894	899	899	894
N. of groups	84	84	84	84	84	84
AR2	0.1919	0.1094	1.2389	0.1903	0.1006	1.1967
AR2 crit. prob.	0.8478	0.9129	0.2154	0.8491	0.9199	0.2314
Hansen J	63.6598	68.7813	68.1293	63.5657	69.7863	66.1618
Hansen df	58	58	58	58	58	57
Hansen crit. prob.	0.2841	0.1572	0.1706	0.2869	0.1381	0.1901
Instruments	75	75	75	76	76	75

Notes: System GMM with Windmeijer correction for standard errors. The dependent variable is Non-Routine Skill Intensity and is an index of industry-level Non-Routine task intensity computed as: (sum of industry Non-Routine cognitive and interactive task inputs)/(sum of routine and manual task inputs). The dependent variable has been computed for three different groups of professions: HS=High-Skill; MS=Middle-Skill; LS=Low-Skill. Med Tech=Medium-Tech dummy; Low Tech=Low-Tech dummy. All regressions are weighted by average employment share over the period 1999-2010. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level. Coefficients for the regression constant and year effects are not reported for sake of simplicity.

Table 5: Effects of Non-Routine Skill Intensity on Wage

Dependent Variable:
Log(Hourly Wage+1)

Model	[1]	[2]	[3]	[4]	[5]	[6]
Emp Sh HS -1	0.1659	0.2395	0.3971***	0.1724***	0.1203*	0.0005
	[0.172]	[0.150]	[0.105]	[0.052]	[0.061]	[0.037]
Emp Sh MS -1	-0.4505***	-0.2086*	-0.3411**	0.0169	-0.048	-0.0486
	[0.099]	[0.119]	[0.138]	[0.031]	[0.046]	[0.048]
Cap Equip -1	0.0312	0.0624***	0.0113	0.0093***	0.0090**	0.0123***
	[0.021]	[0.020]	[0.011]	[0.004]	[0.005]	[0.004]
Imp Pen Hi-Med -3	-0.0388	-0.0623	-0.1725**	0.0510**	0.0034	-0.0084
	[0.074]	[0.091]	[0.084]	[0.021]	[0.023]	[0.016]
Imp Pen Low -3	-0.0318	0.1241	-0.0759	0.0263	0.0402	-0.0322
	[0.063]	[0.112]	[0.088]	[0.018]	[0.028]	[0.020]
NR Intensity HS -1	1.4789***			0.4392**		
	[0.340]			[0.197]		
NR Intensity MS -1		1.2646***			0.0868	
		[0.303]			[0.381]	
NR Intensity LS -1			0.3135*			-0.0901
			[0.164]			[0.061]
Wage HS -1				0.7834***		
				[0.069]		
Wage MS -1					0.8035***	
					[0.080]	
Wage LS -1						0.9065***
						[0.033]
Med Tech				0.0105***	-0.0066	0.0005
				[0.004]	[0.006]	[0.004]
Low Tech				0.0196***	-0.0065	-0.0093
				[0.007]	[0.008]	[0.008]
Observations	899	899	891	899	899	891
N. of groups	84	84	84	84	84	84
R-sq	0.9421	0.9349	0.9146			
AR2				-0.6007	1.4019	-0.2466
AR2 crit. prob.				0.5481	0.1609	0.8052
Hansen J				58.4928	54.9382	30.9883
Hansen df				57	57	37
Hansen crit. prob.				0.4204	0.5528	0.746
Instruments				77	77	57

Notes: Models from [1] to [3] are panel data regressions with fixed effects and robust standard errors adjusted for clustering at the industry level. Models [4]-[6] are System GMM with Windmeijer correction for standard errors. The dependent variable is log of hourly wage and has been computed for three different groups of professions: HS=High-Skill; MS=Middle-Skill; LS=Low-Skill. Med Tech=Medium-Tech dummy; Low Tech=Low-Tech dummy. All covariates, except dummies, have been log-transformed. All regressions are weighted by average employment share over the period 1999-2010. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level. Coefficients for the regression constant and year effects are not reported for sake of simplicity.

Figure 1

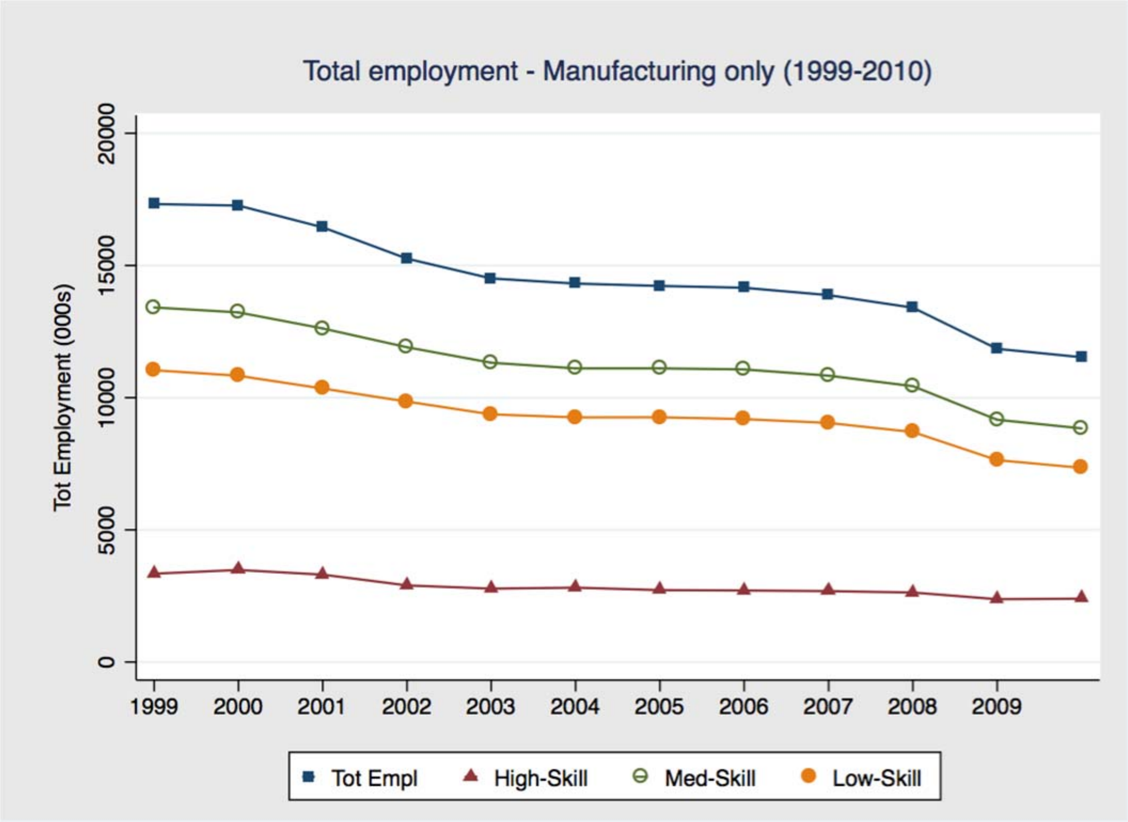

Figure 2

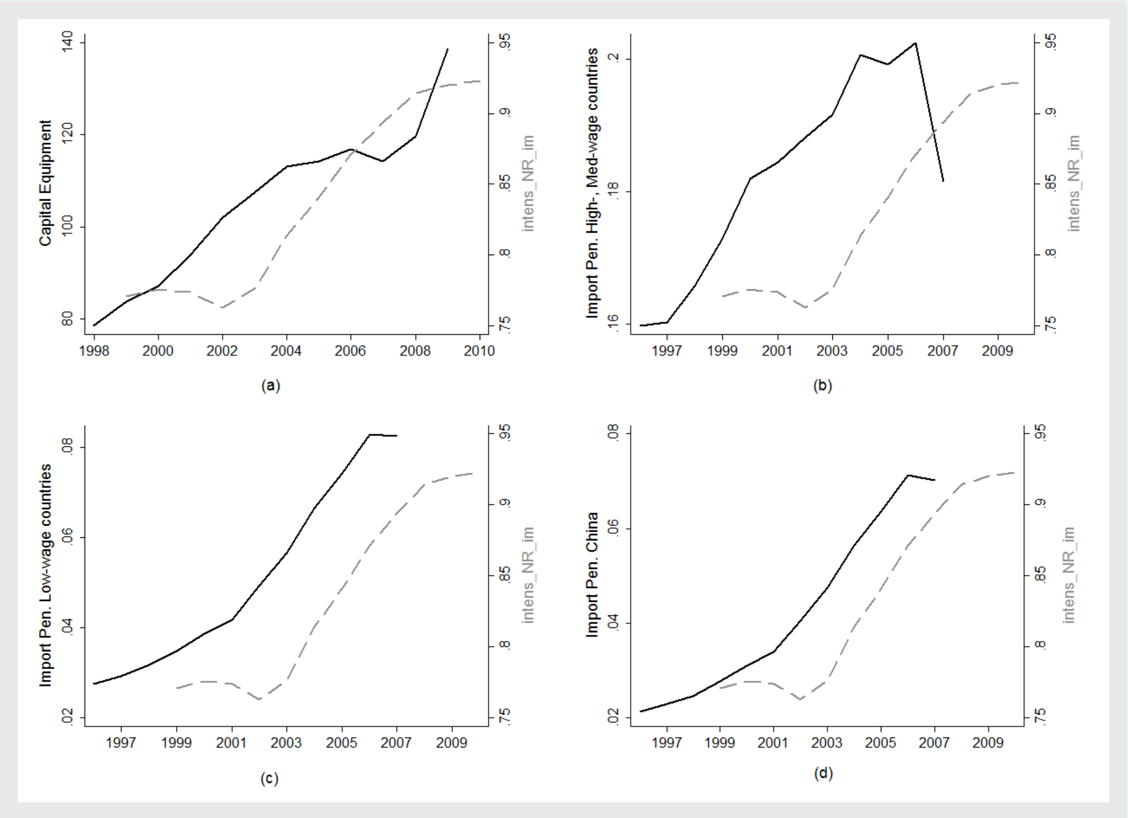

Figure 3

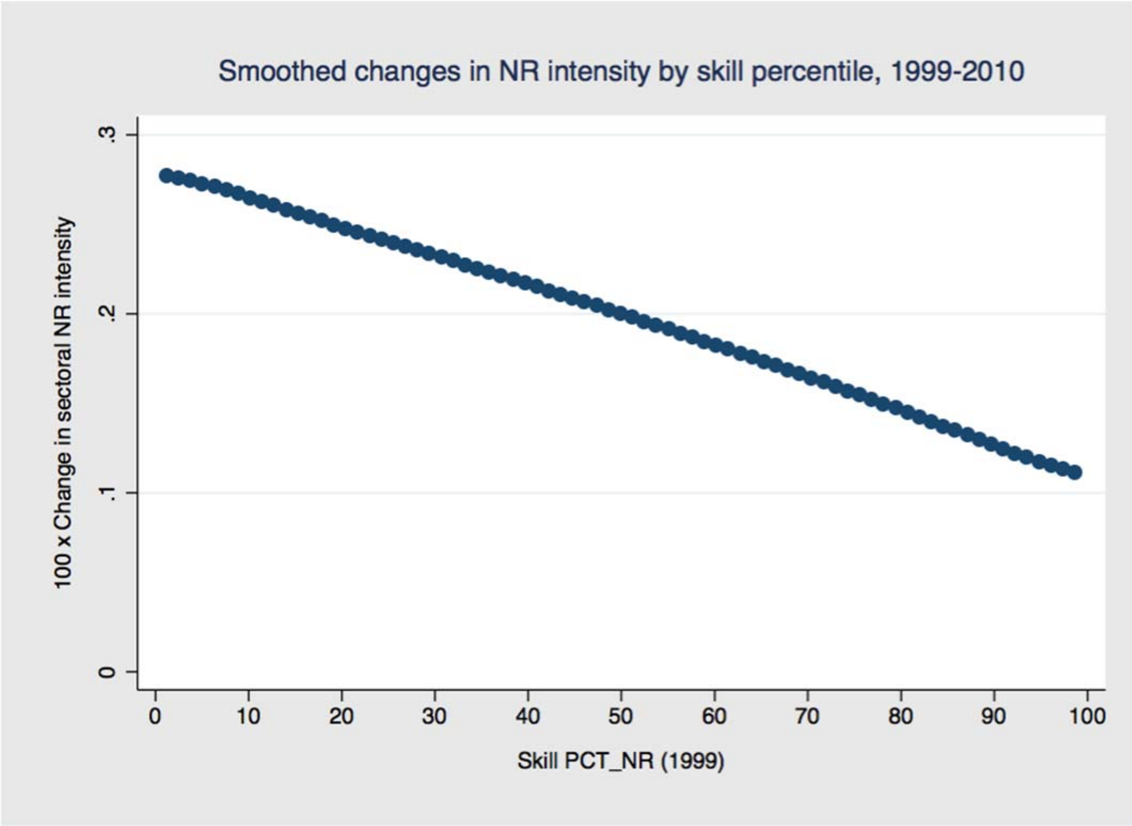

Figure 4: Coefficients with 95% confidence intervals from Table 4 Models 1 through 3.

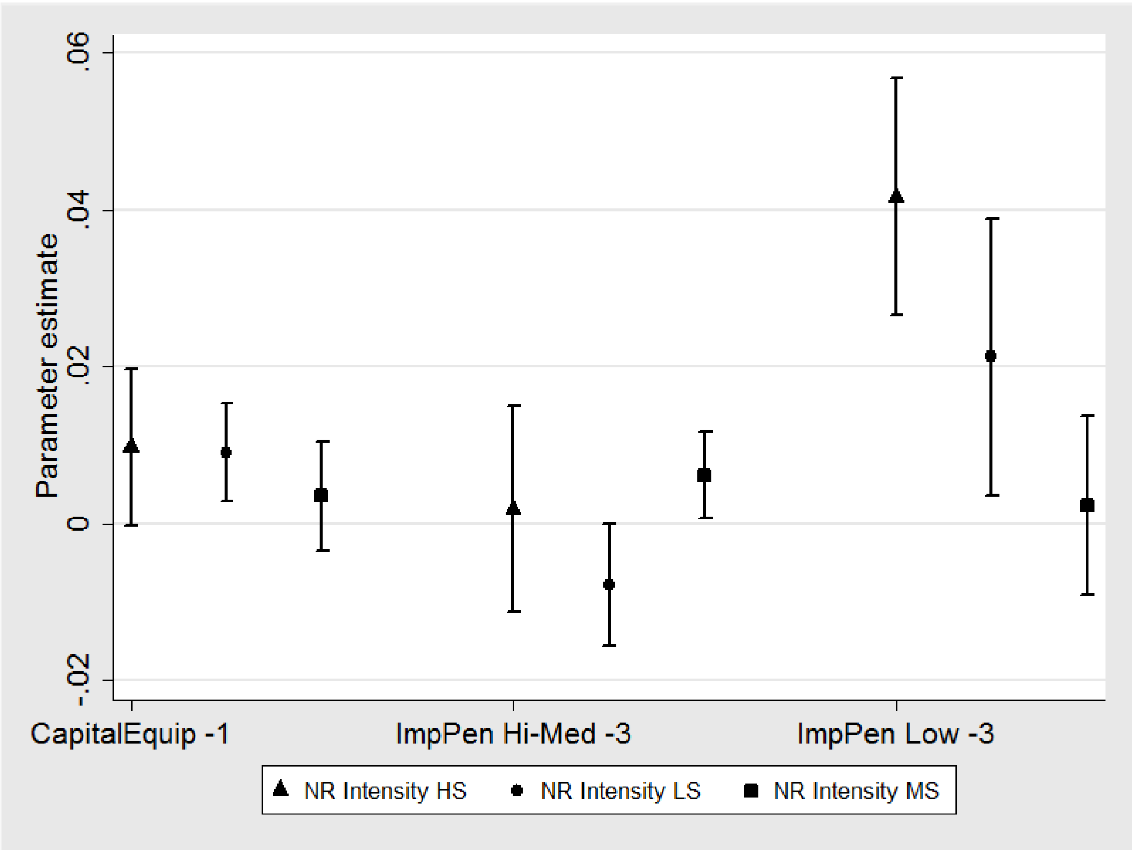

Figure 5: Coefficients with 95% confidence intervals from Table 4 Models 4 through 6.