Professional services delivery changes with firm growth in the US

Edouard Ribes

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October 6, 2018

Abstract

The delivery model of professional services firms is evolving because of trade and technology opportunities. Using a task based framework, it can be estimated that 22% of the content of professional services occupations can either be displaced or replaced. Both opportunities could each impact between 10 to 12% of the overall labor landscape.
However those numbers must be nuanced and embedded in a context of firm growth. This paper therefore proposes a growth blueprint for professional services firms where trade and technology opportunities can be seized in phases depending in firms' size. This notably stresses the difference between small and large firms.
Finally this service delivery model blueprint is used to discuss the overall occupational wage landscape evolution. This paper draws on the US firm size landscape and the existing wage literature to suggest that trade and technology will affect all jobs and increase the wage structure polarization of the US PSFs sector.

2010 *JEL Classification.* L84;F23;F66;L14
Keywords and phrases. Trade; Technological change; Firm growth; Professional services

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1 Introduction.

Context and key questions. The analysis of the firm performance is one of the key strategic research themes in the professional services industry [39]. To perform and be competitive, firms need to adjust their supply to meet the market demand. For professional services firms, which are human capital intensive, this can be done in three ways. The firm can adjust by tapping in its local labor market, by trading work on a global scale [38] or by replacing human labor by technology [40].
However PSFs performance drivers are not the same across the firm life cycle [29]. The initial growth phase of such firms is indeed mainly associated to local factors (i.e within country) [10] with a strong focus on geographical expansion ([35]), which would suggest that growing firms tap into the local labor supply. On the other hand, mature PSFs efforts concentrate on labor productivity and labor differentiation, which suggest that they are likely to leverage trade and technology to supply services to their clients.
If the service delivery options are well known, there is little literature on their importance and magnitude for PSFs along the firm life-cycle, a gap that this article intend to bridge. Finally as trade and technology change the firms demand with respect to the job market, the price of labor (namely wages) is being adjusted at an occupation level. This article therefore proposes directional discussion on the impact of trade and technology on the firm local workforce.

Contribution to economic literature. To reach its objectives, this article builds on three strands of the economic and management literature. First it expands on the notions of trade (notably through off / nearshoring), which is a well - known method to optimize the value chain of a firm ([17], [34]). Trade revolves around performing specific tasks in locations that have competitive labor costs advantages [16] . As per benchmarks, 21% of the US labor can potentially be traded and similar patterns are observed in the EU. Trade affects all jobs and all skills levels [5]. It is approached though a firm level assessment of tasks modularization [15] and their possible displacement in a more competitive location. To assess whether or not tasks can be traded, the literature stresses two main features: the tasks degree of interactivity and the task degree of routine [15]. Initially routine tasks were the primary candidates for trade (e.g standard reporting, payroll administration etc.). However technological change has yet expanded trade opportunities to interactive tasks while more routine tasks have started to be automated, especially in large multi national firms [24]. If the trade literature has been a growing over the last two decades [33], it has yet to be put in perspective with respect to technological change. Additionally, the initial focus of the literature was on manufacturing [20] and there has been little advances, to my knowledge, on the field of knowledge intensive firms ([27]). This article therefore contributes to the trade literature by providing a joint investigation on the impact of trade and technology on the delivery model of PSFs.
Secondly this article expands on the burgeoning economic literature on technological change (notably with respect to computerization/automation), in two scenarios have emerged. On one hand, studies similar to [19] have stated that up to 47% of US labor is subject to technological replacement. On the other hand, more conservative views (such as [2]) estimate the potential labor replacement by technology around 11%. There is yet a consensus on the fact that technology leads to a productivity increase [28] (which has been estimated to be about 11% in the case of manufacturing) and that it leads to a diminution in low complexity tasks [4], which is leading to a skill and wage polarization of the labor market [1]. In the service industry [14], technology has indeed raised the employment in low (resp. high) skills occupations while reducing (resp. increasing) the associated wages. If there has been some discussions on the effect of technology and trade on wage polarization [22], there has been

no estimation of the impact of technology on professional services and its potential overlap with trade. Additionally, neither trade nor technology have been, to my knowledge, discussed in the context of professional services firms growth, a gap this article intend to bridge.
Finally this paper expands on the labor economics literature related to the effect of trade and technology on wages. Initially, differences in wage levels in the US were explained by differences in human capital [37]. The associated models therefore discussed the returns of education and skills for workers. However the rise of trade and technology has required economists to leverage tasks based frameworks, which have enhanced the understanding of the existing wage structure by combining the returns of education and the returns of tasks ([12], [3]). This generated discussions that, at a US economy level, have converged on the fact that both trade an technology lead to a polarization of wages [5]. This has also been stressed through longitudinal empirical studies such as [18]. This phenomenon appears to have been driven by very large firms [21]. However there has been to my knowledge, no specific discussion on the wage structure in the field of professional services. Therefore this paper discusses the occupational shifts related to technology and trade and put them in perspective through a tasks - human capital wage model with respect to the US economy wage polarization.

Article structure. To understand the evolution of a professional service firm delivery model during its growth, this article first start by estimating the trade potential of professional services occupations. It then complements this initial estimation by assessing the amount of work that can be replaced by technology as well as the overlap between labor displacement through trade and labor replacement through technology. This serves as a basis to propose a service delivery blueprint with firm growth, which stresses the differences between small, medium and large PSFs. Finally the shift in professional services occupation tasks profile due to trade and technology is used to discuss occupational wages structure evolution in US PSFs.

Important Legal Remarks. The findings and opinions expressed in this paper are those of the author and do not reflect any positions from any company or institution.

2 Estimation of the impact of trade in professional services.

2.1 Data description and definitions.

To estimate the tradability of jobs in the US professional services industry, the Occupational Information Network (O*NET), developed under the sponsorship of the U.S. Department of Labor/Employment and Training Administration (USDOL/ETA) was used. O*NET describes the jobs in any given industry and maps their features in a standard fashion. Within the professional services sector, O*NET presents 273 different jobs with an average wage ω_j of 35.17\$/h (std 11.91\$/h) and the overall sector employs 7.31M people. The top 5 occupations in terms of employment in the sector cover about 23% of the overall sector employment. They are namely accountants and auditors (461k employees), lawyers (365k employees), software developers (357k employees), secretaries (253k employees) and management analysts (241k employees).
Within O*NET, a job j is assessed on a set of 41 standard work activities a (that are shared across all jobs in the O*NET database) in both importance $I_{j,a}$ and complexity $C_{j,a}$ on a scale from 1 to 100. Activities importance and complexity are used in this article to define two main metrics:

- the overall job j complexity Φ_j which is defined as the importance weighted sum of the job activities complexity:

$$\Phi_j = \frac{\sum_a I_{j,a}.C_{j,a}}{\sum_a I_{j,a}}$$

- the degree of of specialization Ψ_j of job j as the variance in the importance $I_{j,a}$ across the work activities a

From a job content standpoint, professional services wages are not related to the job complexity (Spearman correlation between job complexity Φ_j and its wage ω_j of -9.8%) nor its specialization (Spearman correlation -11.2%). The correlation between O*Net tasks complexity or importance and job wages is low (absolute values of Spearman correlation coefficients are below 20%), which means that individual tasks can not explain wages differences between occupation.
However if individual task importance and complexity do not drive compensation, they drive labor displacement through trade.

2.2 Methodology.

In the initial methodology described by [25], a tradability index was constructed for each job j based on 11 of the 41 work activities in the O*NET database. Each of these activities a was assigned a weight $w_a \in \{-1; 1\}$, where +1 (resp. -1) represented a task that could (resp. could not) be traded. In this framework, O*NET tasks related to information content (i.e. getting information, processing information, analyzing data and information, documenting/recording information) and internet enabled tasks (i.e. interacting with computers) were considered tradable and assigned of weight of +1. On the other hand, face to face or on-site activities (i.e. assisting or caring for others,performing or working directly with the public,establishing or maintaining interpersonal relationships) as well as non routine tasks (i.e. thinking creatively, making decisions and solving problems) were considered not tradable and assigned a weight of -1. The associated Jensen's tradability index Θ_j was then defined as:

$$\Theta_j = \sum_a w_a.(\frac{1}{4} * C_{j,a} + \frac{3}{4} * I_{j,a})$$

Applied to the professional services sector, the Jensen index Θ_j allows a job to job comparison in terms of tradability potential. In this framework, tradability results on the 5 main (from an employment standpoint) professional services activities yet appear counter intuitive. While accountant, auditors and secretaries appears in the lower 25% of the distribution (i.e. low tradability), lawyers, management analyst and software developers appears highly tradable.
These aggregated job level results need to be interpreted carefully. Tasks can be traded but jobs can not. Therefore, rather than having an ordinal measure, a cardinal measure of the impact Δ_j of trade on a given occupation seems more adapted. To build this measure, the same tasks as the one encompassed in the Jensen index are considered. The trade impact on a job is then defined as the overall proportion of tasks (importance wise) that can be traded, such that:

$$\Delta_j = \frac{\sum_a 1_{w_a=1}.I_a}{\sum_a I_a}$$

Note that with this task level definition, tasks complexity is not taken into account, which corresponds to an hypothesis that there is enough skilled labor supply in the host locations to meet the demand in traded tasks. When estimating trade at task level, it comes that within the professional services sector about $\mathbb{E}_j(\Delta_j) = 17\%$ of the overall work performed in the US can be considered displaced. The potential labor displacement ranges from about $min_j(\Delta_j) = 10\%$ (in occupations such as paper hangers, earth drillers etc..) of a job up to $max_j(\Delta_j) = 30\%$ (in occupations such as mathematician technicians, proofreaders, interviewers etc...). From a benchmark standpoint, the proposed estimation on professional services appears in line with the current literature on trade, which estimates that between 11% and 25% of the work in services can be traded [6].

2.3 Tradability effect within professional services.

2.3.1 Occupation level implications.

Trade occurs at task level. Therefore local jobs do not disappear but rather evolve. Trade has three characteristic features with respect to occupations. First, trade potential is no correlated to an occupation wage level. The Spearman correlation between the Jensen's tradibility index (resp. task level tradability) and the job wages is indeed of 0.023% (resp. 4.9%). Second, trade potential is not related to job complexity (Φ_j). The Spearman correlation between the Jensen's tradibility index and the job complexity is indeed low (28%), while the task level tradability Spearman correlation with the job complexity is even lower (-4%). Finally, trade potential increases with job specialization (Ψ_j). The Spearman correlation between the Jensen's tradability index (resp. task level tradability) and the job specialization is indeed of 77% (resp. 56%).
When impacted by trade, local occupations specialization (Ψ_j) increases by an average of 47%. This increase in specialization occurs for 77% of the professional services occupations, while the 23% remaining jobs see on average a specialization reduction of 9.2%. On the other hand, as all the information related tasks are getting displaced, trade in professional services creates occupations in host locations that are heavily specialized on data extraction, transformation and analysis. Note that the displacement of information related tasks present a "hollowing-out" risk as mentioned by [27]. However this is not a topic that will be tackled in this paper.

2.3.2 Firm level implications.

Besides occupation level consequences, trade effects on professional services is different from the effects on manufacturing, around which the economic literature has historically revolved. Professional services establishments are indeed 4 times smaller on average than manufacturing ones. As 90% of the professional services establishments employ less than 60 people ([35]), the trade potential at an establishment level is limited. 17% of 60 people indeed represents 12 FTEs, which is about the threshold for a local PSF to consider opening a new establishment. Trade being mainly a cost optimization lever, small growing firm will most likely first focus on market expansion and trade will only start to be leveraged as part of medium or large firms strategy (i.e about 3 establishments, more than 120 - 180 FTE).When looking at the US PSFs landscape, those implementation considerations mean that trade actually impacts very few firms but has a significant effect on the overall US employment. According to the 2015 statistics of the US census bureau, the total professional services sector (NAICS code 54) indeed counted a total of 799986 firms of which 789172 (i.e. 99%) had less than 100 employees. But this 1% of firms that can benefit from trade actually employ 4.95M people (i.e. 56% of total employment).
Those firm level considerations have two consequences. First, trade can potential offset the projected employment growth in professional services proposed by the US bureau of labor statistics. Currently

the sector is indeed projected to growth by 9.6% on average of the next 10 years, but if 56% of the labor market is subject to a 17% local reduction in labor because of trade, this means that the overall US professional services labor market will remain flat or even slightly decrease. Second trade will lead to an occupational polarization across the labor market. Jobs within large firm will indeed be much more specialized than those in small ones and will be complemented by information workers in a multi local model. As for a same occupation, firm level differences will increase and so will wages differences. Trade therefore impacts all occupations categories and has the potential to displace about 17% of the US professional services labor. However this can only be enabled in firms that have reach a sufficient size and is therefore a disruptor that only impact half of the US labor market. As trade concerns mainly information related tasks, it has yet to be discussed in a context of technological change.

3 Discussing the impact of labor displacement and replacement in professional services.

If the redistribution of labor across different locations has attracted interest in the research community, it is also important to consider the impact of technological change on occupations (notably through automation), when assessing the potential evolution of the professional services delivery. Labor displacement indeed mainly revolves around information related tasks that have a high technological replacement potential ([2]).

3.1 Replacing labor by capital - impact of technology in professional services.

To estimate the potential of technological replacement within professional services, a two steps approach was followed. First 15 tasks out of 41 in the O*NET taxonomy were identified as potentially impacted. Those tasks were given a weight $w_a^c = 1$, while the others were given a weight of $w_a^c = 0$. The potentially replaced tasks were of 3 types. First, 2 physical tasks could potentially be automated : "operating vehicles, mechanized devices, or equipment"; "handling and moving objects". Second, tasks that are information related were also considered subject to technological replacement: "documenting/recording information" ; "getting information"; "processing information"; "evaluating information to determine compliance with standards"; "analyzing data or information"; "estimating the quantifiable characteristics of products, events, or information". Finally control and monitoring tasks were also considered to have replacement potential: "controlling machines and processes"; "inspecting equipment, structures, or material"; "performing administrative activities; organizing, planning, and prioritizing work"; "scheduling work and activities"; "monitor processes, materials, or surroundings"; "monitoring and controlling resources".
It was then assumed for a job j that those tasks could only be automated if their complexity was below a given threshold $\hat{C}$. In the case of professional services, 25% of the tasks have a complexity below 39, while 50% of the tasks have a complexity below 54%. In this case, the complexity threshold for technological replacement $\hat{C}$ was therefore assumed to be $\hat{C} = 50$, which could be perceived as a technology friendly view (i.e. mid complexity tasks can be automated). This led to the following measure Γ_j of the impact of technology on job j:

$$\Gamma_j = \frac{\sum_a 1_{C_a < \hat{C}} . w_a^c . I_a}{\sum_a I_a}$$

With the proposed methodology, the average technological replacement impact on professional services job $\mathbb{E}_j(\Gamma_j)$ was of 9.9% with a standard deviation of 7.1%. It ranged from 1% (on occupations such

as epidemiologists, psychologists, survey researchers) up to 30 to 35% (on jobs such as file clerks, messengers, demonstrators and product promoters). Technology had a very different effect across the top 5 employment categories: secretaries and assistants automation potential was of 23%, software developers showed a 13% automation potential while lawyers, management analysts, auditors and accountant automation potential was below 5%.
Finally the job level overlap between tradability and technological replacement β_j was defined as the amount of traded tasks that can be automated:

$$\beta_j = \frac{\sum_a 1_{C_a<\hat{C}}.w_a^c.1_{w_a=1}.I_a}{\sum_a I_a}$$

Interestingly, the overlap between labor replacement and labor displacement is small. On average ($\mathbb{E}_j(\beta_j)$), in professional services, 5.5% (standard deviation of 3%) of the jobs content is both subject to displacement and to replacement. The overall Spearman correlation between the overlap and the tradability impact is of -1.6%. This means that technological replacement is not linked to tradability but rather acts as a disruptor on both tradable and non tradable work. From a benchmark standpoint, note that the proposed estimates for professional services appear in line with the latest body of literature that estimate the potential impact of technological replacement to be about 5% to 10% of the overall workforce in OECD countries ([2]).

3.2 Technological change effect within professional services.

As tasks get replaced, jobs evolve. This potential evolution is not related to the current level of wages nor to the average job complexity. The occupation level Spearmann correlation between technological replacement potential and wage (resp. complexity) is indeed of 1.92% (resp. -3.9%). However technological replacement is, by definition, highly correlated to the average job complexity (-82.2%). As technology delivers on low complexity labor, occupations becomes more specialized (specialization (Ψ_j) indeed increases by 117% on average). However on average, jobs do not become more complex. Replacing labor increases the complexity (Φ_j) of half of the occupations by about 2%, while decreases the complexity of the rest of the occupations by about 2% as well. Therefore replacing labor through technology does not entail a focus on more complex and value added tasks for workers. It is indeed more of a scaling mechanism where capital is invested by firms to increase their delivery capabilities with sub-linear costs.
Technology can be perceived as an instrument of growth for large professional services firms ([35]) that have reached a size sufficient to industrialize their services. Because technological replacement can only cover 10% of a firm labor needs, for technology to be prioritized over market expansion (worth about 12 FTEs), the firm must have a workforce at least larger than 100 FTEs. As only 1% of the US PSFs firm have more than 100 employees (see (2.3)), service delivery industrialization is a change driven by few actors which reinforces their leadership position. As a future avenue of research, tt would be interesting to investigate to which extent services industrialization affects the balance of large and small professional services firms.
Finally note that at an occupational level, the combination of trade and technology leads to a reduction in local labor that can range from 12% to 40%. The total trade and technological impact is estimated to be above 40% for the following 5 jobs: Mathematical Technicians,Electronic Drafters, Bookkeeping,Accounting, and Auditing Clerks, Proofreaders and Copy Markers, Mapping Technicians. On the other side, the lowest cumulated impact of trade and technology is around 12% and is achieved for the following 5 occupations: explosives Workers, Ordnance Handling Experts, and Blasters; Architects,

Except Landscape and Naval; Biochemical Engineers; Industrial-Organizational Psychologists; Urban and Regional Planners.

3.3 Professional services firm cost of services delivery blueprint.

In light of the discussion around labor displacement and replacement developed in sections (3.1) and (2.2), a 4 phases cost management blueprint for professional services could be proposed. On the demand side, the blueprint assumes that PSFs generate about 80$ per hour of work ([36]), that displaced work entails a 10% discount to this rate and that the work delivered by technology comes at the same cost as the work delivered by a human being. Note that those pricing assumptions are illustrative only and would require a deeper discussion that is out of scope of this article. On the supply side, it is assumed that employees work about 260 days per year and have a 50% labor productivity (i.e. the amount of time they spend billing clients). As discussed in section (2.2), 17% of PSFs work is assumed to be tradable, 10% can be automated and there is a 5% overlap between tradability and technological replacement.
Under those assumptions, the proposed blueprint (summarized in figure (1)) consists of:

- Phase I: PSFs grow locally until up to 120 FTEs or about 10M$ of revenue at which point they do have enough tradable work (worth an equivalent of 10 to 20 employees) to open a new establishment in a location that presents an interest from a cost standpoint. At this stage, there is not enough replacement potential to invest capital in technology.
- Phase II: PSFs grow in multi local fashion. As they share some of the benefits of their multi local model with their clients, their revenue growth becomes slower.
- Phase III: As PSFs start to reach the local 200 FTEs milestone (or about 18M$ of revenue per year), replacement opportunities becomes tangible in the local workforce.
- Phase IV: When PSFs reach the local 1500 FTEs milestone (or about 130 M$ of revenue), the work that was previously displaced has enough potential to be replaced, which slows the employment growth of the multi local model.

Note that the development of a multi local model raises a governance question around the firm intent to either displace labor in house (e.g. build a captive offshore center) or to outsource it. As per [30], this decision appears to be mainly related to an assessment of the firm capabilities, a topic that is out of scope of this article. The proposed blueprint appears yet in line with the current literature [33] that argue that labor displacement is marginal for small firms that are more focused on market expansion, while medium to large firms have a high focus on maintaining their profitability level and engage in a systematic review of their resources allocation. Trade and technology associated changes impact about 50% of the US professional services workforce. If their impact on occupations content has already been discussed in the previous sections for the firm, it is now important to discuss to which extent trade and technology will impact individual workers, notably in terms of compensation.

4 Estimation job wages polarization in PSFs based on tasks decomposition.

Labor displacement and labor replacement have triggered a shift in the labor economics literature related to individual compensation. Initially, the driving economic factor to explain wages differences

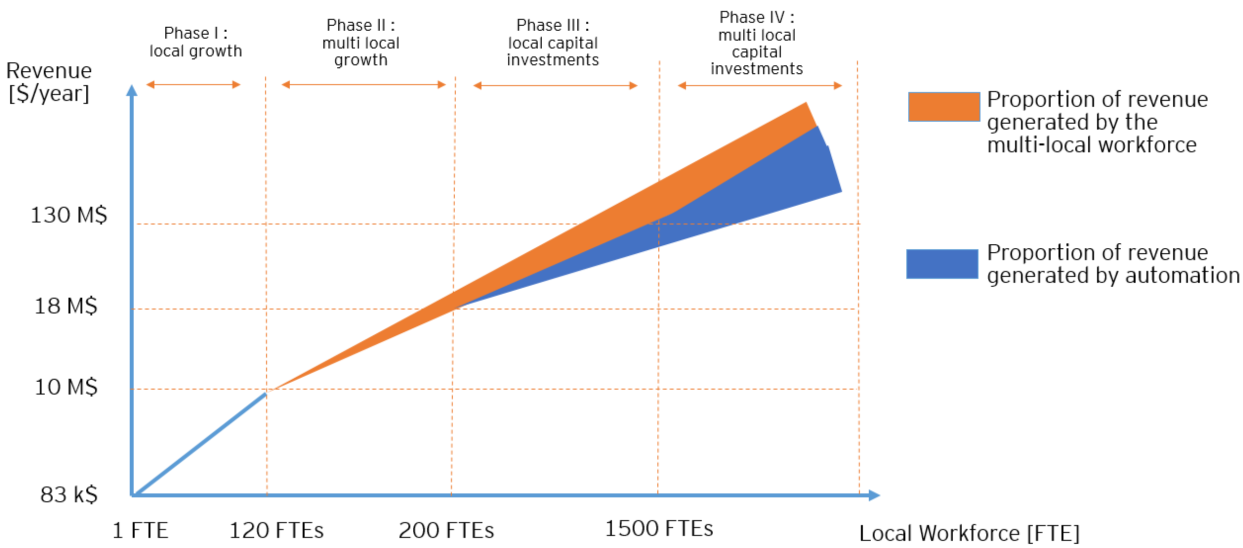

Figure 1: US PSFs - cost of delivery blueprint.

was human capital [37], which was expressed in terms of educational achievements and skills. This notably informed discussions around the US wage structure evolution over the past century. This has yet proved insufficient to explain the recent US wage structure polarization [21]. Therefore tasks level considerations ([12],[3]) have been used to show the polarization effect of trade and technology [18]. This section will build on those ideas to discuss the wage polarization within the professional services sector.

4.1 A proposal of a task based wage model.

As a benchmark, professional services wages can be modeled via the method developed by [3], which is inherited from the [1]. Under this framework, O*Net tasks were categorized as abstract, routine or non-routine manual, their importance averaged and the following regression was used to assess the impact of tasks importance on wage w_i in an occupation i:

$$log(w_i) = a + b * Abstract_i + c * Routine_i + d * Manual_i + \epsilon_i \tag{1}$$

Running this analysis on O*Net wage data in the context of professional services doesn't however yield significant results. None of the parameters appear significant (see table (1)) and the regression yields a R^2 of 1% and an AIC of 229.

The idea behind this benchmark model (1) is to aggregate the information related to tasks in intuitive categories that explain wages differences. However, the proposed decomposition appears inappropriate in the context of professional services. From a correlation standpoint, abstract, routine and manual tasks exhibit a 8% correlation level with professional services wages, which is on par with each of the individual O*Net tasks. The intuitive decomposition thus comes with a loss of information. On the other hand, explaining the professional services wages across the 273 occupations based on all the 40+ O*Net tasks importance and complexity scores does not yield significant results either.

A more efficient approach is to decompose professional services in a linear combinations of tasks that can capture most of the inter occupation tasks variance. This can be done for example through a principal component analysis (PCA). In essence, the idea is similar to the clustering performed by [3] but trade manual combinations with a clear interpretation with automated tasks combinations that represents sub-sections of jobs or roles. When running a PCA, it appears that 95% of the variance in tasks within the 273 PSFs related occupations can be captured in 10 roles, which are used in the rest of this article to understand the link between the wage level w_i of occupation i and the occupation scores $s_{j,i}$ on the first 10 most important roles R_j generated within the professional services sector. This generated the equation 2, which was augmented with the occupation i trade potential (Ψ_i) and labor replacement potential (Γ_i) defined in the previous sections.

$$(w_i) = a + \sum_{j=1}^{j=10} (b_j * s_{j,i} * R_j) + c * (\Psi_i) + d * (\Gamma_i) + \epsilon_i \tag{2}$$

The results displayed in table (1) show that the role based regression (eq. 2) outperforms the initial methodology described through (eq. 1). If the role based regression in only able to capture 20% of the inter occupation wage variance, the occupations decomposition on those 10 roles is significant. It also shows that trade potential can be significantly linked to the current differences in wages levels across occupations, but that labor replacement does not.

The fact that labor replacement does not appear to have a significant role on occupation wage level could mean that the returns of technology at a task level are the same than the returns of a worker. This appears in line with the proposal that technology in professional services is merely a growth enabler and that by investing in technology, large firms don't stretch the labor market supply and avoid competing for workers to meet the client demands (which would mean increasing their direct costs and lowering their profit). On the other hand, trade potential appears to have a significant role in explaining inter occupation wages differences. The higher the trade potential, the higher the wage level of an occupation. This means that non traded work comes at a premium in the US. This would have to be further investigated through a longitudinal study to see over time if the local premium has been decreasing as the competition with more cost efficient location increases.

4.2 Future of work and wages polarization.

4.2.1 Evolution of the US labor market for professional services.

The statistics of the US business published by the US census bureau report on a yearly basis both the overall payroll structure by firm size as well as the overall employment in the professional services sector. In the US, as of 2015, there was an important difference in average wages with respect to firm size in professional services. Firm of less than 100 employees had an average yearly wage of 71k$ per employee while larger firms had an average wage of 91k$ per employee. This gap of about 30% in average wage with respect to firm size is a known fact that has been documented in numerous studies [9]. However the gap in the professional services sector appears to be higher than the current 20% that was documented as the US economy level [8].

This gap is yet increasing, which is a different pattern than the one exhibited in the overall US economy, where those gaps are shrinking. Leveraging the data from 2009 to 2015, the standard deviation of the average wage per employee across all firm sizes has systematically increased on a year on year basis by 0.21 k$ per year. While the average pay per employee over the entire sector has grew by 2.08k$ per year (i.e a year on year increase of about 2.6% for an average wage of 80k$ per employee per year in 2015), small firms (i.e less than 50 employees) year on year pay increases have been smaller at 1.64k$/year than those of medium counterparts (i.e. between 50 and 300 employees) at 2.35k$/year.

However the pattern doesn't seem to hold for firms with more than 300 employees that have seen a yearly increase in wage of 2.11k$/year.
As a general rule, the average wages differences between small and large firms have been explained by the differences in compensation of managerial jobs [31]. As the firms grows, the firm indeed adds managerial layers, which increases the compensation of the upper tail of the wage distribution. However, this doesn't explain why there is a difference in the wages of the medium size firms are rising more quickly than those of their larger counterparts.

4.2.2 Impact of trade and technology on occupational wages: a discussion.

Leveraging the regression of (2) and assuming that trade and technological replacement have occurred, it is possible re-project the occupation tasks profile on the predefined roles R_j and therefore to estimate the associated shift in wage structure across occupations in the US professional services landscape. The associated results are presented in figure (2).
Trade leads to a reduction of wages across the entire occupation spectrum and leads to the development of a local low wage workforce. On the other hand, technology has the opposite effect. It increases wages and narrows down the gap between high and low wage occupations. When combined, the effects of trade appears to have the upper hand on most occupations as a low costs workforce emerges. As a result, the average wage across professional services occupations decreases by about 2$/h, while the minimal wage across occupations decreases by about 56% (from 11.03$/h to 6.2$/h). Knowing that the minimum wage at a national US level is set at 7.25$/h, this means that the development of the low cost services may need to be framed by policies. If technology mitigates some of the trade effects, it drives a positive change for the highest paying job in the industry. For example, the maximum average wage increases by about 2% (from 66.9$/h to 68.3$/h). This means that overall trade and technology lead to a polarization of the labor market related to professional services, which is similar to the overall effects observed across the entire US economy in [32] and [5].This polarization of the wage structure also comes with a standardization in terms of wages with respect to medium wage occupation. This effect is mainly driven by technology and is aligned with the ideas of [13] that state that technology comes with a delayering of firms' management structure.
The employment consequences of labor displacement and replacement are yet not covered by the proposed model. According to [11], employment increases (resp. decreases) for local workers that are focusing on complex (resp. routine) tasks. However, this would have to be put into perspective with respect to professional services demand and supply, notably with respect to distribution of large and small PSFs, a topic that won't be covered in this paper. Those occupations level compensation considerations can be used to propose an explanation for the observed increasing differences between small and large firm compensation in professional services. As most occupations are seeing an average wage reduction because of trade, the increase in small and large firms average wage differences could mean that large firms labor composition is shifting toward more value added high wage occupations. This yet means that small professional services firms could have either provide services to the entire economic landscape or provide specific low costs services to bigger professional services firms, which raises a question in terms of outsourcing.

5 Conclusion.

In this article, it was estimated that in the US professional services, 17% of the labor can be traded and that 10% of it can be replaced by technology. The overlap between trade and technological change

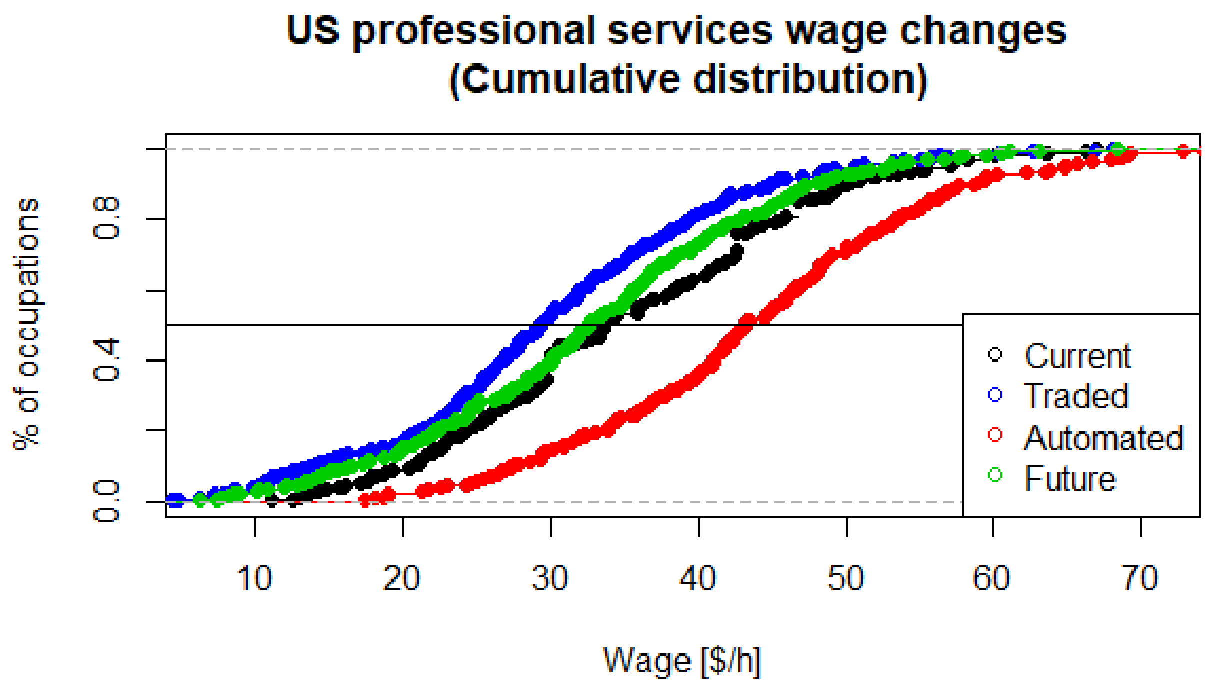

Figure 2: US PSFs - wage evolution due to tradability and automation in large firms.

was valued at 5%. This appears in line with existing results at a US economy level. However the impact of trade and technology is not the same across all firms. For professional services, a blueprint was proposed where trade only starts to impact medium sized firms, while automation opportunities comes at a latter stage for large firms. These differences were used to discuss wage evolution at an occupation level. It was shown that technology and trade create higher job standards and leads to a wage structure polarization within large firms.

In terms of next steps, three topics would require some attention. First, the impact of trade in professional services rates would need some consideration. The benefits generated by changes to the service delivery model should indeed be shared with the clients [23], which could probably lead to a change in the balance between small and large firms. This would notably have to be discussed with respect to the impact of trade on the quality of services [38]. Second the notion of technological change would benefit from some standardization. It would notably help to understand the amount of capital that is required to invest in technology, which would help fine tune the proposed PSFs growth blueprint. Finally if trade and technology have implications on average jobs wage levels, it would be important to consider to which extent they impact the wage distribution within occupations as well as occupation level employment.

6 Acknowledgments.

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7 Appendix.

Variables in (eq.2)	Estimate (Std.)	Variables in (eq.1)	Estimate (Std.)
a	25.03 (5.15)	a	36.41 (2.01)
b_1	-0.85 (0.25)	b	0.034 (0.045)
b_2	-0.25 (0.09)	c	-0.053 (0.035)
b_3	0.032 (0.01)	d	0.037 (0.054)
b_4	-0.054 (0.02)		
b_5	0.27 (0.11)		
b_6	1.34 (0.47)		
b_7	-0.73 (0.33)		
b_8	0.11 (0.05)		
b_9	0.05 (0.02)		
b_{10}	-0.82 (0.38)		
c	56.12 (28.77)		
d	-6.99 (10.60)		
R^2	20%	R^2	1%
AIC	1851	AIC	2133

Table 1: Wage models parameters estimation