A Structural Estimation of the Employment Effects of Offshoring in the U.S. Labor Market

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Abstract

In this paper, we generalize the Grossman and Rossi-Hansberg (2008) offshoring model to include numerous tasks/skill levels and then empirically investigate the effect of offshoirng on occupational employment for ten major occupational groups (at 2-digit SOC level) in the U.S. labor market using the CPSMORG (Current Population Survey Merged Outgoing Rotation Groups) data from year 1983 to 2011. We first use the non-parametric monotonic cubic spline interpolation method to approximate offshoring cost functions. Results show that among the ten occupational groups, those involved with more impersonal and/or routine tasks have relatively lower offshoring costs in comparison to groups involved in more personal and/or non-routine manual tasks. Based on estimated offshoring costs, we then focus our analysis on five relatively more offshorable occupational groups to further calculate the number of jobs offshored as well as the offshoring percentage by occupation over the sample period. Results indicate: i) production occupations are most offshorable among all five offshorable occupational groups; ii) the offshoring percentage for production occupations has been increasing over time; and iii) offshoring percentages for professional occupations, management, business, and financial operations occupations have been decreasing over time.

Key words: Offshoring, Employment, Monotonic Cubic Spline Interpolation, Offshoring Cost

JEL classification: F14, F16, C14

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1. Introduction

The debate over offshoring intensified in the United States when offshoring spread from the jobs of blue-collar workers in manufacturing sectors to those of white-collar workers in service sectors. Service sectors comprise about 80 percent of the U.S. employment and most white-collar workers are employed in the service sector. U.S. workers in all sectors became more concerned about the security of their jobs due to increased offshoring activities as the global economy continued to integrate. A well-educated radiologist and a low-skilled automobile assembly line worker could both be susceptible to offshoring. These concerns are reflected in results from Princeton University's telephone survey conducted in summer 2008.[1] Survey results indicate occupational offshorability reported by individual survey respondents are much higher than those predicted by economists.

The wide-spread offshoring along with a persistently high unemployment rate in recent years, heightened policymaker concerns and has been the subject of increased economic research on the short- and long-run labor market implications of offshoring, in particular, the potential for U.S. job loss. The actual impact of offshoring is multi-dimensional and difficult to quantify. Existing empirical estimates (Bardhan and Kroll, 2003; Blinder 2007; Blinder 2009) provide a wide range of estimates for offshorable jobs in the U.S. labor market, varying from 11 to 47 percent. With relatively little theoretical guidance, the wide range in early empirical estimates provided limited information to policymakers facing tensions from a high national unemployment rate exceeding 9 percent.

[1] For details, see Blinder and Kruger (2009).

Under such circumstances, an economic theory of offshoring has been exposited by Grossman and Rossi-Hansburg (2008). In their parsimonious framework, job tasks are defined as either low-skilled or high-skilled. Using comparative static analysis, they then analyze the synergic action of *productivity effect*, *relative-price effect* and *labor supply effect* of offshoring on these two groups due to a change of offshoring costs. Results show that offshoring might lead to wage gains for both low-skilled and high-skilled workers and create a win-win situation for all types of workers, but not necessarily reward one player by harming the others as stated in the traditional Stolper-Samuelson results. Motivated by these results, several papers empirically tested the effect of offshoring in the U.S. (Harrison and McMillan, 2010; Ebenstein et al., 2013; Crinò, 2010b) and in European countries (Goos et al., 2010; Crinò, 2010a; Criscuolo and Garicano, 2010).

Harrison and McMilan (2010) estimated a reduction of four million jobs in U.S. manufacturing employment due to offshoring over the period of 1982 to 1999. Ebenstein et al. (2013) found the impact of offshoring on U.S. worker's wage has been underestimated by previous studies because offshoring has driven workers away from high-wage manufacturing jobs to low-wage service jobs. In addition, workers performing routine tasks are most affected by offshoring and experience larger wage decline. On the other hand, by studying the effects of service offshoring on white-collar employment in more than 100 U.S. occupations, Crinò (2010 b) showed i) service offshoring increases employment in more skilled occupations relative to less skilled occupations; ii) at a given skill level, service offshoring penalizes offshorable occupations while benefiting less-offshorable occupations. However, evidence from European countries is mixed. Goos et al. (2010) found offshoring was associated with reduced employment in offshorable occupations across 16 European countries as opposed to Crinò (2010 a)'s finding that service offshoring has no effect on employment in Italian firms. Using occupational licensing as a shifter of offshoring costs, Criscuolo and Garicano (2010) found an increase in service offshoring increased both wages and employment in less-offshorable service occupations (i.e., licensed occupations) in UK.

Grossman and Rossi-Hansberg's theoretical framework includes wage implications and may partially release policymaker concerns over increased wage inequality due to offshoring in the U.S. labor market, but it does not address the core question of to what extend offshoring will affect labor demand. Goos et al. (2010) did link offshoring as one of the explanatory factors affecting the conditional demand for labor at different occupations in their theoretical model and estimation, but other existing studies simply extend their empirical investigation to the effects of offshoring on either wage or employment or both and provide some empirical evidences.

In this paper, we generalize Grossman and Rossi-Hansberg (2008)'s offshoring model to include numerous tasks/skill levels (tasks correspond to specific occupations in our empirical framework) and investigate the effect of offshoirng on occupational employment for ten major occupational groups (at 2-digit SOC level) in the U.S. labor market (see Table 1.1 and 1.2 for details of occupational groups). Using the CPSMORG (Current Population Survey Merged Outgoing Rotation Groups) data from year 1983 to 2011, [2] we conduct our analysis in two phases. First, the monotonic cubic spline interpolation method is used to estimate the offshoring cost functions for all ten

[2] The entire sample period is separated into pre-2000 (1983-1999) and post-2000 (2000-2011) period because the CPS changed the occupational classification system in 2003 (See details in Section 4). To balance the span of pre- and post-2000 period, year 2000-2002, dual coded in both occupational classification system are included in the post-2000 period for analysis. .

occupational groups. The monotonic cubic spline interpolation method requires no specific functional form other than the assumption that offshoring costs are non-decreasing in the percentage of tasks being offshored. Next, the five relatively offshorable occupational groups are used to further calculate in each occupational group, the number of jobs offshored as well as the offshoring percentage over the sample period.

Aside from a limited number of studies with primary information on offshoring activities (see for example, Crinò, 2010), researchers have used two alternative approaches for measuring offshoring. The first approach is to approximate or infer offshoring activities using relevant information. For example, Ebenstein et al. (2013) use foreign affiliate employment of U.S. multinational firms as a measure capturing U.S. firms' offshoring activities. Criscuolo and Garicano (2010) use occupational licensing to infer the offshorability of an occupation in their study of offshoring of UK service sectors. Approximation of offshoring activities circumvents the issue of time-invariance of offshoring/offshorabilty index, but reliability of the approximation is unknown.

The second approach is to generate a time-invariant offshoring index based on firm offshoring activities. For example, Goos et al. (2010) construct an occupational offshorability index based on offshoring activities of 415 European firms during 2002 to 2008. Applying a time-invariant index assumes that the offshoring activities are either not influenced by the reduction of offshoring costs or that costs are constant over time. A time variant offshoring index is thus especially important when investigating the effect of offshoring over a relative long-time span. For example, the occupation of a radiologist would be considered as non-offshorable without the advancement in recent telecommunication technology which makes transformation of large image data an easy task. An important contribution of this paper is to provide estimates of offshoring for more than 400 major U.S. occupations over the period of 1983 to 2011.

2. A Structural Model of Offshoring

Inspired by empirical findings about the impact of characteristics of tasks on wage inequality and employment structure (e.g. Autor, Levy and Murnane, 2003), Grossman and Rossi-Hansberg (2008) proposed a theoretical model of task offshoring to explain the impact of offshoring on the wage rates of different types of workers. In the Grossman and Rossi-Hansberg model, tasks are limited to only two types: low-skill and high- skill. Under a standard Heckscher-Ohlin set-up, Grossman and Rossi-Hansberg (2008) show how changing offshoring costs will affect the wage rates of low-skilled and high-skilled workers in the home country through static comparative analysis.

We generalize the analysis to include numerous tasks and link the concept of tasks to detailed occupations that are actually offshored. While the focal point of Grossman and Rossi-Hansberg (2008) is to decompose different effects of offshoring on factor prices i.e., wage rate, we focus on exploring the effect of offshoring on employment at different occupations. To be consistent and comparable with Grossman and Rossi-Hansberg (2008), we continue to use the term "task" instead of "occupation" in the model setup, but freely change between these two in the remaining of this paper depending on the context. [3]

2.1 Model Set Up

The production process requires many types of tasks and each type of task is

[3] Each task corresponds to an occupation in our empirical framework.

denoted by o. Producing one unit of specific good involves a continuum of each type of task. Without loss of generality, the measure of each type of task can be normalized to one.

Firms in the home country can produce many goods. The number of goods produced in home country is assumed to be larger than the number of types of tasks.[4] All tasks are involved in order to produce one unit of specific good,[5] i.e., a_{oj} is the total amount of domestic factor o that would be needed to produce a unit of good j in the absence of any offshoring. Firms can undertake an o-type task either at home or abroad depending on the offshoring costs and the relative wage of task o between home and foreign country. An o-type task is indexed by $i \in [0,\ 1]$ and ordered in a manner such that the offshoring cost of task o, denoted by $t(i)$, is non-decreasing in i.

2.2 Model Derivation

As some tasks are more difficult to offshore than others, offshoring costs are assumed to be varying across different tasks and changing over time. Denote offshoirng costs shifter as $\beta_{o,s}$ with subscrip o indicating task type and s indicating time period . Let $w_{o,s}$ and $w^*_{o,s}$ be respectively the home and foreign wage of task o. Then the relative wage between home and foreign country of each task o, denoted by $\omega_{o,s}$, satisfies $\omega_{o,s} = \frac{w_{o,s}}{w^*_{o,s}}$ for all periods s.

Following Grossman and Rossi-Hansburg (2008)'s formulation, $I_{o,s}$, the equilibrium marginal task o performed at home (or the cutoff point of task o at

[4] This assumption is to guarantee a unique solution to the factor price of each type of task given the price and production technology of each good.
[5] If the cost-minimizing demand for factor o is zero, the o-type task will be missing in the production process.

equilibrium) in period s in each industry is determined by the following condition such that wage savings just balance the offshoring cost of task o:

$$w_{o,s} = w^*_{o,s}\beta_{o,s}t\left(I_{o,s}\right). \quad (1)$$

Then by our relative wage assumption $\omega_{o,s} = \frac{w_{o,s}}{w^*_{o,s}}$, I get

$$t\left(I_{o,s}\right) = \frac{\omega_{o,s}}{\beta_{o,s}} = \rho_{o,s}, \quad (2)$$

where $\rho_{o,s}$ denotes the equilibrium offshoring costs, which depends on the ratio of relative wage $\omega_{o,s}$ and the offshoring cost shifter $\beta_{o,s}$ at each period s. Given that $t(\cdot)$ is an increasing function in $I_{o,s}$, more proportion of task o will be offshored overseas as $I_{o,s}$ increases. As $I_{o,s}$ is the cutoff point of the marginal task o performed at home country, $\rho_{o,s}$ precisely captures the offshoring decisions made by home firms.

Denote L_o the initial total employment of occupation o at home country without offshoring, $L_{o,s}$ the employment of occupation o in period s with offshoring, which is observed in data, then $L_{o,s}$, can be calculated as following:

$$L_{o,s} = \left(1 - I_{o,s}\right) \cdot L_o, \quad (3)$$

where $1 - I_{o,s}$ indicates the fraction of o-type tasks that are performed at home.

Now, under the perfect competitive assumption, the price of any good j is equal to the unit cost of production (if a positive quantity of the good is produced):

$$p_j = \sum_o w_{o,s}\Omega\left(I_{o,s}\right)a_{oj}(\cdot), \qquad (j > o) \quad (4)$$ [6]

[6] Equivalent to Equation (3) in Grossman and Rossi-Hansberg (2008). See Section I for detailed derivation.

where, the arguments in the function for the factor intensity a_{oj} (suppressed for the time being) are the relative costs of the various sets of tasks when they are located optimally with offshoring,

and $\Omega(\mathrm{I}_{\mathrm{o,s}}) = 1 - \mathrm{I}_{\mathrm{o,s}} + \frac{\int_0^{I_{o,s}} t(i)di}{t(I_{o,s})}$. (5)

In other words, $\Omega(\mathrm{I}_{\mathrm{o,s}})$ consists of two parts, $1 - \mathrm{I}_{\mathrm{o,s}}$ is the proportion of tasks remained in home country and $\frac{\int_0^{I_{o,s}} t(i)di}{t(I_{o,s})}$ is the proportion of tasks conducted in foreign country expressed in equivalent home-country factor employment.

As $I_{o,s} = \frac{L_o - L_{o,s}}{L_o} = 1 - \frac{L_{o,s}}{L_o}$ is a function of L_o, $\Omega(\mathrm{I}_{\mathrm{o,s}})$ is a function of L_o.

Due to the number of the goods is larger than the number of factors $(j > o)$, factor prices$\left(w_{o,s}\Omega(\mathrm{I}_{\mathrm{o,s}})\right)$ can be uniquely determined and solved from the systems of equations (4). That is,

$w_{o,s}\Omega(\mathrm{I}_{\mathrm{o,s}}) = c_o$, (6)

where c_o depends on the prices p_j and all production technologies of all goods produced in home country. Identity (6) is the key equation we are interested in. From which, we are able to identify the equilibrium cutoff point of offshoring percentage $(\mathrm{I}_{\mathrm{o,s}})$ of task o, offshoring cost $t(i)$ as well as constant c_o. We discuss in details how to proceed to estimate Equation (6) in next Section.

2.3 Model Interpretation

Although Grossman and Rossi-Hansberg (2008) model is completely static, it can be interpreted with some dynamics within each period. Given the wage differential between home and foreign country, the equilibrium cutoff point of offshoring $I_{o,s}$ is determined by Equation (1) at the beginning of period s, which automatically determines the domestic labor demand for task o (in Equation (3)). By the zero-profit condition under perfect competition, we can then obtain a new wage $w_{o,s}$ for task o in period s in the home country by solving Equation (4) (or equivalently Equation (6)). If the new wage $w_{o,s}$ is higher (or lower) than the starting wage in period s, the firm in home country increases (or decreases) offshoring until it reaches its new equilibrium cutoff point at the end of period s that we observe in the data. The same process repeats in all periods.

By this interpretation, we explicitly assume the wage and employment observed in our data set are equilibrium wage and employment at the end of each period, which are both driven by offshoring. Then by estimating Equation (6), we can identify the offshroing cost function $t(i)$[7] and the initial employment without offshoring for each task o.

3. Estimation Framework and Method

3.1 The Empirical Framework

To estimate Equation (6), we first take logarithm and reorder, which leads to,

$$lnw_{o,s} = -ln\Omega\left(\mathrm{I}_{\mathrm{o,s}}\right) + lnc_o = lnc_o - ln\Omega\left(\mathrm{I}_{\mathrm{o,s}}\right). \tag{7}$$

As $\Omega(\ \mathrm{I}_{\mathrm{o,s}})$ is a function of observed variable $L_{o,s}$, unobserved parameters L_o and the offshoring cost function $t(\cdot)$, standard linear estimation methods are not applicable.

Further denote $y_{o,s} = \ lnw_{o,s}$, $x_{o,s} = L_{o,s}$. Then the conditional mean of $y_{o,s}$ can be correctly specified as

[7] However, the offshoring cost function $t(i)$ can only be identified up to a constant scale because multiplying a scalar to $t(i)$, Equation (6) still holds.

$$E(y_{o,s}|x_{o,s}) = m(x_{o,s}, \boldsymbol{\theta_0}) = lnc_o - ln\Omega\left(\ \mathrm{I}_{o,s}(L_{o,s}, L_{o,}t(\cdot))\right) \tag{8}$$

where $\boldsymbol{\theta_0} = (L_o, c_o\ , t(\cdot))$ consists of two parameters and one function to be identified. Since $\boldsymbol{\theta_0}$ contains the offshoring cost function that cannot be directly estimated, we need to parameterize $t(\cdot)$ in order to proceed to estimate $t(\cdot)$ together with the other two parameters.

No specific structure except the monotonicity of $t(i)$ (i.e., $t(i)$ is non-decreasing in i) is assumed in the Grossman and Rossi-Hansberg (2008)'s framework. Hence, attaching any specific functional form to the offshoring cost function $t(i)$ in our theoretical model and using a parametric estimation method, will likely result in misspecification problems.[8] Instead we adopt the non-parametric cubic spline method, in particular, the monotonic cubic spline interpolation method to approximate the offshoring cost function$t(i)$.

Once parameterization of $t(\cdot)$ is resolved, estimation of equation (8) becomes a standard non-linear estimation problem. The NLS estimators

$$\boldsymbol{\theta} = min_{\theta\in\Theta}\, N^{-1}S^{-1}\sum_{o=1}^{N}\sum_{s=1}^{S}\left\{y_{o,s} - m(\boldsymbol{x}_{o,s}, \boldsymbol{\theta})\right\}^2 \tag{9}$$

minimize the sum of least squared residuals of the sample average and will solve the sample minimization problem if the true parameters $\boldsymbol{\theta_0} = argmin_{\theta\in\Theta}E\{[y - m(x, \boldsymbol{\theta})]^2\}$ solves the population minimization problem.

Ideally we would estimate Equation (8) occupation by occupation to identify the initial employment without offshoring L_o at home country, the constant parameter c_o and

[8] We experimented with different functional forms for $t(i)$ such as linear, quadratic, cubic, exponential as well as exponential multiplied by a linear function. Unfortunately, results are not only very sensitive to the initial values that are chosen but also easy to reach extreme solutions: corner solutions of *I*.

the set of parameters for each occupation o in the parameterized offshoring cost function $t(i)$. Due to data restrictions, [9] we group the individual occupations into ten broad occupational groups for pre- and post-2000 period respectively and use these as the basis to estimate Equation (8).

3.2 Application of Monotonic Cubic Spline Interpolation Method

In this paper we use a two-step monotonic cubic spline interpolation procedure to estimate $\widehat{\boldsymbol{\theta}} = \left(L_o, c_o, t(i)\right)$ based on the algorithm of monotonic cubic spline interpolation developed by Wolberg and Alfy (1999, 2002). While it is often used in the field of economics, monotonic cubic spline interpolation is a well developed method and widely used in numerical and statistical data analysis to solve many engineering problems. The most compelling reason for the use of cubic polynomials is the property of twice differentiable continuity, which guarantees continuous first and second derivatives across all intervals. The goal of cubic spline interpolation is to determine the smoothest possible curve that passes through designated control points while simultaneously preserving the property of piecewise monotonicity within each interval.

The algorithm of Wolberg and Alfy (2002) is adopted in our first step, which also consists of two steps. We name their steps the Wolberg and Alfy Algorithm Step-1 and Step-2 to distinguish from our two-step procedure and avoid confusion. The Wolberg and Alfy Algorithm Step-1 attempts to find a twice continuously differentiable cubic spline which minimizes the modified second derivative discontinuity in the spline.[10] If a

[9] See data description for details.

[10] Definition of second derivative discontinuity: $\sum_i \left[f''(x_i^-) - f''(x_i^+)\right]^2$. Definition of modified second derivative discontinuity: summation of second derivative difference is non- negative, i.e., $\sum_i \left[f''(x_i^-) - f''(x_i^+) + K\right] \geq 0$, where K satisfies $f''(x_i^-) - f''(x_i^+) + K \geq 0$ for any arbitrary i. The reason to use modified second derivative discontinuity is

twice continuously differentiable cubic spline exists, the Wolberg and Alfy Algorithm Step-2 is then employed to obtain the optimal twice continuously differentiable cubic spline by computing the integral of the spline curvature. If not, the best first differentiable cubic spline is obtained in the Wolberg and Alfy Algorithm Step-1 and the Wolberg and Alfy algorithm Step-2 is canceled.

In our first step, we partition $i \in [0,\ 1]$ into ten even sub-intervals, representing the percentage increment of i being offshored. I use the Wolberg and Alfy Algorithm Step-1 and Step-2 to locally approximate the offshoring cost function $t(i)$ and obtain the monotonic cubic spline interpolation by updating the initial values of the cost function $t(i)$ at each control point of i [11] for each occupational group. In our second step, we use the interpolated offshoring cost function to calculate $\Omega\left(\ \mathrm{I}_{o,s}\left(L_{o,s}, L_{o,} t(\cdot)\right)\right)$ in Equation (3.9). Then we minimize the non-linear least square errors by iterations to obtain the optimal estimators of $\widehat{\boldsymbol{\theta}}$. $\widehat{\boldsymbol{\theta}}$ is a vector containing 13 estimators. They are estimator of the initial employment of occupation o at home country without offshoring $\hat{L}_o$, estimator of the constant parameter $\hat{c}_o$ and the set of estimators for parameterized offshoring cost function $t(i)$, which corresponds to 11 control points that portioned $i \in [0,\ 1]$ into ten even sub-intervals.

3.3. Estimating Offshoring Cost Functions for the Ten Major Occupational Groups

To implement the monotonic cubic spline approximation of the offshoring cost functions for the 10 major occupational groups, we need some initial starting point for $t(\cdot)$. We use Blinder and Kruger (2009)'s estimated offshorability in major occupational

to turn the objective function into a linear function so that linear programming can be applied. Please see Wolberg and Alfy (2002) for details.

[11] The 11 control points of i are 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8., 0.9, 1.

groups[12] as the starting point to differentiate relatively offshorable occupations from relatively non-offshorable occupations.[13] Based on their externally-coded estimates, we divide the 10 occupational groups into two broad categories: Offshorable Groups (Table 2) and Non-offshorable Groups (Table 3).

Table 2: Offshorable Groups

Rank of Offshorability	Occupational Group (Externally-coded Offshorable Percentage)
1	G9:Production Occupations[14] (80.7)
2	G5:Office and Administrative support occupations (41.2)
3	G2:Professional and related occupations (20.5)
4	G4:Sales and related occupations (17.8)
5	G1:Management, business, and financial occupations (16.4)

Notes: Prepared by authors based on the externally-coded offshorable percentage (Column 2, Table 2) in Blinder and Kruger (2009).

Table 3: Non-offshorable Groups

Rank of Non-offshorability	Occupational Group (Externally-coded Offshorable Percentage)
1	G6: Farming, fishing, and forestry occupations (0.0)
1	G7: Construction and extraction occupations (0.0)
1	G10: Transportation and material moving occupations (0.0)
2	G3: Service occupations (0.7)
3	G8: Installation, maintenance, and repair occupations (1.3)

Notes: Prepared by authors based on the externally-coded offshorable percentage (Column 2, Table 2) in Blinder and Kruger (2009).

[12] See Table 2, Column 5, titled Externally-Coded Percent Offshorable in Blinder and Kruger (2009).

[13] There are sharp disagreements between self-classified and externally coded offshorability for some occupational groups. I choose to use the externally-coded offshorability by professionals as my criteria to divide offshorable and non-offshorable groups.

[14] For the purpose of simplicity and comparability with Blinder and Kruger (2009)'s results, only post-2000 occupational group titles are used to indicate occupational groups in the main text unless otherwise specified.

3.4. Estimating Number of Jobs Offshored and Offshoring Percentage

We focus on the five offshorable occupational groups in Table 2 to calculate the number of jobs offshored as well as the offshoring percentage by detailed occupation in pre- and post-2000 sample period as we do not control for factors that could potentially affect the occupational employment other than offshoring (e.g. technology, institutional restructuring) in our empirical work. While this is a strong assumption, it is more realistic for the relatively offshorable occupations which is our primary focus.

To calculate the number of jobs offshored and the offshoring percentage for the five offshorable occupational groups over the pre- and post-2000 sample period, we need to use $\hat{L}_o$, which is estimated from the adjusted employment size $\tilde{L}_{o,s}$ of each occupation from the two-step cubic spline interpolation, to recover $\tilde{L}_o$, the unadjusted initial employment without offshoring for each occupational group by reversing the adjusting method.

By estimating Equation (8) for each occupational group instead of occupation by occupation, the parameter L_o (i.e., the initial total employment without offshoring for each occupational group) is assumed to be same for all occupations within a group. This is a relatively strong assumption for the 10 occupational groups with large between-occupation variations in employment within each occupational group. In order to identify L_o and obtain a meaningful $\hat{L}_o$ for each occupational group, we need to adjust employment size for each occupation and make occupations relatively homogenous within an occupational group.

The estimated $\hat{L}_o$ largely depends on the maximum or minimum value of the adjusted employment $\tilde{L}_{o,s}$ within each occupational group. The estimated $\hat{L}_o$ is likely to be misleadingly inflated if there are extreme values of $\tilde{L}_{o,s}$ within an occupational group. Hence, we drop the upper and lower five percentile observations of the adjusted employment to further homogenize the employment size for the five offshorable occupational groups and re-estimate the cost functions.

We apply different scenarios for these five offshorable occupational groups when re-estimating the offshoring cost functions, calculating number of jobs offshored and offshoring percentage. Based on Blinder and Krugerman (2009)'s estimates for offshorable occupational groups (re-organized in Table 2), we start with the 20% scenario for all five groups as a benchmark case because the externally coded offshorability for Group 1 (Production Occupations, 16.4%), Group 2 (Professional Occupations, 20.5%) and Group 4 (Sales Occupations, 17.8%) are relatively close to 20 percent. In the 20% scenario, we assume that the offshoring percentage does not exceed 20 percent of the maximum $\tilde{L}_{o,s}$, i.e., the estimated $\hat{L}_o \leq 1.2 * max(\tilde{L}_{o,s})$., We then gradually relax the maximum offshoring percentage to 40 percent (the externally coded offshorable percentage is 41.2 percent for Group 5, Office and Administrative Support Occupations) and 80 percent (externally coded offshorable percentage is 80.7% for Group 9, Production Occupations) for all five offshorable groups.

4. Data Description and Adjustment

The CPSMORG (Current Population Survey Merged Outgoing Rotation Groups) data from years 1983 to 2011 is used to implement the two-step monotonic cubic spline interpolation procedure. Although the entire period covers from1983 to 2011, the data is discontinuous due to a complete switch in the occupational and industrial classification system in CPS in 2003.[15] This substantial change in the composition of detailed occupations between the 1980 and 2002 occupation codes makes linking data by occupation codes impossible. Hence, we break the sample into two periods: pre-2000 (1983-1999) and post-2000 period (2000-2011) to conduct analysis at occupational level.

Observations for individuals with age less than 18 and or more than 65 are dropped from the sample to maintain focus on the labor force. Hourly wage series for each individual is created following Schmitt 2003 and inflated by 2000 CPI index to obtain the real hourly wage. Wage and employment are aggregated to occupation level based on 1980 census codes for the pre-2000 period and based on 2002 census codes for the post-2000 period. CPS earning weights are used to obtain occupational hourly wage while CPS final weights are used to obtain occupational employment during aggregation. To maintain balanced panels for both pre- and post-2000 period, occupations not present in all years of each analysis period are dropped. After aggregation, there are 486 occupations in the pre-2000 period and 460 occupations in the post-2000 period (Table 1.1 and 1.2).

Several adjustments are made to reduce between-occupation variations and homogenize the employment size within each occupational group. For both pre- and post-2000 sample period, mean employment for each occupation and median employment for all occupations within an occupational group is calculated . Relative employment size for each occupation is mean employment of each occupation by this occupational group

[15] Year 2000-2002 are dual-coded in both 1980 and 2002 census classifications systems.

median employment.[16] Finally, the adjusted employment for each occupation in each year $\tilde{L}_{o,s}$ is observed employment divided by the relative employment size of each occupation. The adjusted employment for each occupation $\tilde{L}_{o,s}$ is used in the monotonic cubic spline interpolation to approximate the offshoring cost function.

5. Results and Discussion

5.1 Offshoring Costs for the Ten Major Occupational Groups

Estimated offshoring cost functions indicate that among the 10 occupational groups, Group 1 (Management, business, and financial occupations), Group 2 (Professional and related occupations), Group 4 (Sales and related occupations), Group 5 (Office and Administrative support occupations) and Group 9 (Production occupations) have relatively lower costs at any given level of offshoring percentage i in both the pre- and post-2000 periods. In particular, production occupations in Group 9, which are commonly regarded to be containing most impersonal and/or routine tasks and easiest to offshore, have the lowest offshoring costs when offshoring percentage is below 40 percent. The remaining five occupational groups, Group 3 (Service occupations), Group 6 (Farming, fishing, and forestry occupations), Group 7 (Construction and extraction occupations), Group 8 (Installation, maintenance, and repair occupations) and Group 10 (Transportation and material moving occupations), have relatively higher offshoring costs.

Most of our results in both pre- and post-2000 period are consistent with the externally coded offshorability of Blinder and Krugerman (2009) based on individual

[16] If there are even-numbered groups within an occupational group, we use the larger of the two medians as the denominator.

telephone survey in 2008. Blinder and Krugerman (2009) found Group 6 (Farming, fishing, and forestry occupations), Group 7 (Construction and extraction occupations) and Group 10 (Transportation and material moving occupations) to be the least offshorable. Our results identified farming, fishing, and forestry occupations (Group 6), construction and extraction occupations (Group 7), and service occupations (Group 3) with the highest offshoring costs.

5.2 The Five Offshorable Occupational Groups

Instead of comparing the results of the five occupational groups within the same scenario, and comparing the results of the sample occupational group among three different scenarios,[17] we use the externally coded offshorability estimated for the five offshorable groups from Blinder and Krugerman (2009) (reorganized in Table 3) as a criterion and select results of the 20% scenario for Group 1, Group 2 and Group 4, the 40% scenario for Group 5, and the 80% scenario for Group 9 to make comparison. This comparison shows that occupations in office and administrative support group (Group 5) have relatively low offshoring costs among the five offshorable occupational groups, and this trend is clearer in the pre-2000 period (Figure 1 and 2).

Initial total employment without offshoring for each offshorable occupational group is recovered from the estimated $\hat{L}_o$ to calculate the number of jobs offshored and the offshoring percentage over time. The initial total employment for each occupation o in each year s within an offshorable occupational group is derived by multiplying the relative employment size of each occupation to its corresponding $\hat{L}_o$ that it belongs. The

[17] For each offshorable occupational group, offshoring cost function, number of jobs offshored and offshoring percentage are calculated under the 20%, 40% and 80% scenario. Detailed results for all three different scenarios are available upon request.

number of jobs offshored for each occupation o in each year s is the difference between the initial total employment of occupation o we recovered and the observed $L_{o,s}$. The offshoring percentage is then obtained using the number of jobs offshored divided by the initial total employment without offshoring. The number of jobs offshored and the average offshoring percentage at occupational group level for the 20% scenario for Group 1, Group 2 and Group 4 with the 40% scenario for Group 5 and the 80% scenario for Group 9 [18] in both pre- and post-2000 period are summarized in Table 4. The evolution of offshoring percentage for the five occupational groups is further illustrated in Figure 3.

Even though the results for pre- and post-2000 period are displayed in parallel, it is not feasible to make a direct comparison of the jobs offshored and/or the offshoring percentage for a particular occupational group between pre- and post-2000 because the compositions of occupations within each occupational group for pre- and post-2000 period are completely different. Nonetheless, we can still observe the trend of the change of offshoring percentage for the five occupational groups over time. Our calculated offshoring percentage for Group 1 (Management, business, and financial operations), Group 4 (Sales occupations) and Group 2 (Professional occupations) are much higher than the externally coded offshorability estimates by Blinder and Krugerman (2009). The offshoring percentage of production occupations in Group 9 has been consistently increasing over the time for both pre- and post-2000 periods. Under the 80% scenario, if maximum of 80 percent of production occupations are offshorable, offshoring percentage for production occupations increases from 37 percent to 50 percent in the pre-2000 period, and increases from 49 percent to 62 percent in the post-2000 period, which are less than

[18] The initial total employment under all three scenarios, the number of jobs offshored and the offshoring percentage under other scenarios not reported in Table 4 are available upon request.

the estimated 80.7 percent by Blinder and Krugerman (2009). For office and administrative support occupations (Group 5) and sales and related occupations (Group 4), their overall offshoring percentages are relatively stable over both sample periods. On the other hand, results indicate that for management, business, and financial operations (Group 1) and professional and related occupations (Group 2), offshoring percentages actually have decreased over the time in both pre- and post-2000 period.

6. Conclusion

In this paper, we generalize the Grossman and Rossi-Hansberg (2008) offshoring model to include numerous tasks/skill levels. This generalization allows us to link the theoretical task offshoring model directly to occupational data that can be aggregated from the CPSMORG (Current Population Survey Merged Outgoing Rotation Groups) data from year 1983 to 2011. We then empirically investigate the effect of offshoirng on occupational employment for ten major occupational groups (at 2-digit SOC level) in the U.S. labor market by estimating their offshoring cost functions using a non-parametric monotonic cubic spline interpolation method. Based on the estimated offshoring costs, we identify five relatively offshorable occupational groups including production occupations, office and administrative support occupations, sales and related occupations, professional and related occupations, and management, business, and financial operations occupations.

Motivated by the practical issue of difficulty in obtaining a time-variant offshoring/offshorability index faced by majority empirical studies interested in identifying the effect of offshoring, we further calculate the offshoring percentage for the five relatively offshorable occupational groups under different scenarios. Our calculated offshoring percentage provides time-variant offshoring indices for more than 300 major detailed occupations in these five relatively offshorable groups that can be employed in other empirical studies.

Results show that offshoring percentage for each occupational group may vary under different scenarios, but the evolution pattern is consistent. We find production occupations are most offshorable among all five offshorable occupational groups in all three scenarios. We also find that the offshoring percentage for production occupations has been increasing in both pre- and post-2000 period while the offshoring percentages for professional and related occupations, and management, business, and financial operations occupations have been decreasing over time.

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Table 1.1: Major Occupational Groups in pre-2000 Period: 1983-1999

Group	1980 Census Codes	Occupation Title	Number of Occupations
1	003-037	Managerial and professional Specialty occupations	24
2	043-199 203-235	Professional specialty occupations Technical occupations	126
3	403-469	Service occupations	42
4	243-285	Sales occupations	23
5	303-389	Administrative support occupations	55
6	473-499	Farming, forestry, and fishing occupations	19
7	553-599 613-617	Construction trades Extractive occupations	35
8	503-549	Mechanics and Repairers	27
9	633-699 703-799	Precision Production Occupations Operators, fabricators, and laborers	99
10	803-889	Transportation and Material Moving Occupations	39
Total			486

*Notes: Occupational group information is obtained from (http://usa.ipums.org/usa/volii/98occup.shtml), but reorganized and reordered by author to be comparable with occupational groups in post-2000 period.

Table 1.2: Major Occupational Group in Post-2000 Period: 2000-2011

Group	2002 Census Codes	Occupation Title	Number of Occupations
1	0010-0950	Management, business, and financial operations occupations	42
2	1000-3540	Professional and related occupations	107
3	3600-4650	Service occupations	57
4	4700-4960	Sales and related occupations	17
5	5000-5930	Office and administrative support occupations	50
6	6000-6130	Farming, fishing, and forestry occupations	8
7	6200-6940	Construction and extraction occupations	36
8	7000-7620	Installation, maintenance, and repair occupations	34
9	7700-8960	Production occupations	75
10	9000-9750	Transportation and material moving occupations	34
Total			460

*Notes: Occupational groups are equivalent to those grouped at 2-digit SOC level.

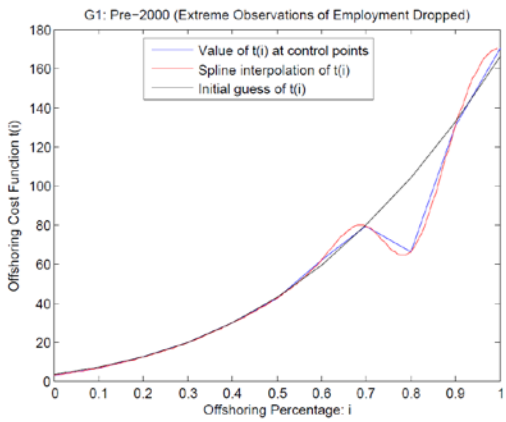
Table 4
Calculated Number of Jobs Offshored and Offshoring Percentage for Five Offshorable Occupational Groups

	Year	Group 1 (20%)		Group 2 (20%)		Group 4 (20%)		Group 5 (40%)		Group 9 (80%)	
Pre-2000	1983	9,805,640	45.4%	15,520,778	46.2%	7,243,396	33.0%	12,258,023	42.1%	7,897,501	37.1%
	1984	9,025,388	43.1%	16,121,095	46.6%	7,181,916	33.0%	13,678,316	42.9%	8,196,717	38.0%
	1985	9,180,988	43.5%	16,129,226	45.4%	7,371,503	32.2%	13,472,866	42.6%	8,259,837	37.9%
	1986	8,571,104	40.9%	15,605,335	45.2%	7,127,393	29.6%	13,203,501	41.5%	8,338,369	38.7%
	1987	8,064,392	39.4%	16,345,036	45.2%	6,770,840	27.6%	13,298,992	42.4%	8,393,546	40.2%
	1988	7,209,673	37.5%	16,212,468	44.0%	6,671,750	29.4%	13,225,815	41.2%	8,623,326	40.1%
	1989	6,488,364	34.3%	15,664,572	42.8%	6,276,374	29.0%	13,353,895	40.5%	8,471,306	39.0%
	1990	6,554,819	34.8%	14,848,548	42.1%	5,812,511	25.7%	13,195,936	38.6%	8,471,054	40.3%
	1991	6,262,801	32.8%	14,670,161	39.4%	5,993,540	28.0%	13,268,496	37.5%	8,662,996	40.9%
	1992	8,541,574	33.3%	14,085,842	40.0%	5,899,998	26.9%	12,597,215	38.3%	8,847,216	42.7%
	1993	8,108,863	31.9%	13,360,689	39.4%	5,758,459	25.4%	12,876,149	37.1%	8,951,068	44.0%
	1994	7,970,182	33.2%	13,706,086	39.4%	6,850,031	30.3%	15,128,418	43.4%	9,902,134	46.7%
	1995	7,283,743	31.5%	12,926,290	38.1%	6,569,780	27.8%	15,426,189	43.0%	9,709,962	45.5%
	1996	6,865,596	29.9%	12,186,064	37.2%	6,291,958	29.0%	14,720,002	42.3%	9,717,579	47.1%
	1997	6,222,981	30.5%	11,535,810	36.2%	5,871,853	27.9%	14,487,004	40.8%	9,898,104	47.4%
	1998	5,766,171	28.4%	11,019,256	36.0%	5,717,374	28.3%	14,377,179	41.2%	9,947,928	48.0%
	1999	5,342,644	25.8%	10,004,199	35.1%	5,825,226	28.1%	14,417,794	42.0%	10,080,191	49.5%
Post-2000	2000	9,488,042	34.6%	14,435,412	39.9%	7,237,264	30.5%	12,072,715	37.3%	9,435,558	49.0%
	2001	9,328,081	33.8%	14,026,210	38.6%	7,088,081	30.3%	12,178,911	38.7%	10,069,160	51.4%
	2002	8,364,073	35.2%	14,101,064	39.1%	6,980,427	30.2%	12,641,911	42.6%	10,735,309	54.6%
	2003	8,651,100	36.2%	13,849,768	37.0%	7,012,221	27.2%	12,868,015	37.3%	11,407,537	53.8%
	2004	9,100,723	35.9%	13,620,745	36.9%	6,932,649	29.0%	13,074,952	38.2%	11,648,598	56.3%
	2005	9,123,268	33.4%	13,488,178	36.5%	6,652,860	27.5%	13,054,829	37.5%	11,776,083	56.5%
	2006	8,576,751	32.8%	13,323,473	35.6%	6,519,848	28.1%	13,117,474	38.5%	11,877,235	58.0%
	2007	8,029,615	30.5%	12,754,427	34.9%	6,420,453	26.6%	13,362,358	41.9%	11,981,270	59.6%
	2008	7,613,932	31.0%	12,449,851	35.6%	6,864,375	30.7%	13,049,624	40.8%	11,858,124	59.7%
	2009	8,026,866	29.6%	12,212,905	34.0%	6,868,086	32.3%	13,449,911	43.1%	12,542,491	61.2%
	2010	8,393,559	29.7%	12,204,844	33.5%	7,349,687	33.8%	13,312,392	43.4%	12,622,064	61.8%
	2011	8,437,689	31.4%	11,911,440	34.7%	7,090,338	32.1%	13,709,638	42.6%	12,572,409	62.0%

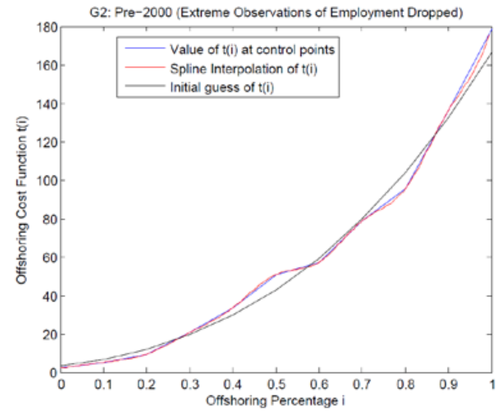
Notes: 1. In 20%, 40% and 80% scenario, offshoring is set not to exceed the 20% , 40% and 80% of the maximum adjusted employment of all occupations across all years within each occupational group respectively.
2. The number of job offshored is the sum of job offshored across all occupations within an occupational group.
3. The offshoring percentage is the average offshoring percentage across all occupations within an occupational group.

Figure 1: Pre-2000 Period (1983-1999)
Offshoring Cost Function for Five Offshorable Occupational Groups

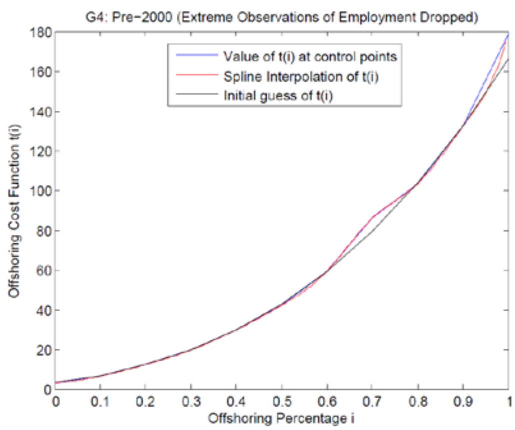
Group 1 (20% Scenario)



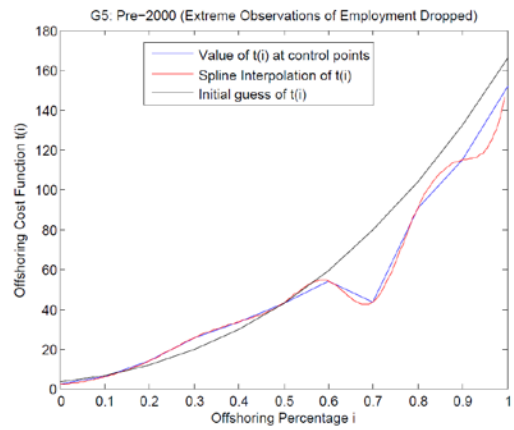
Group 2 (20% Scenario)



Group 4 (20% Scenario)



Group 5 (40% Scenario)



Group 9 (80% Scenario)

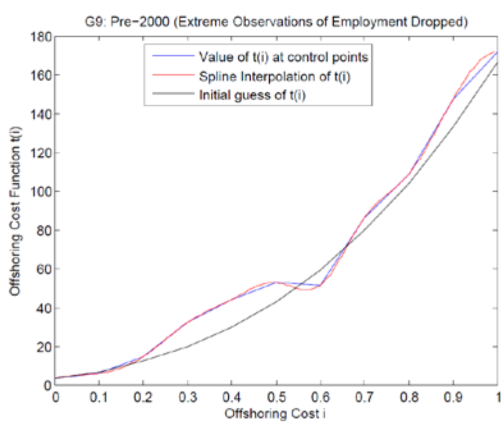
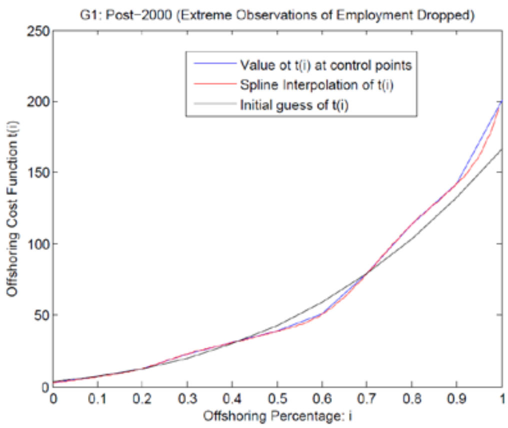
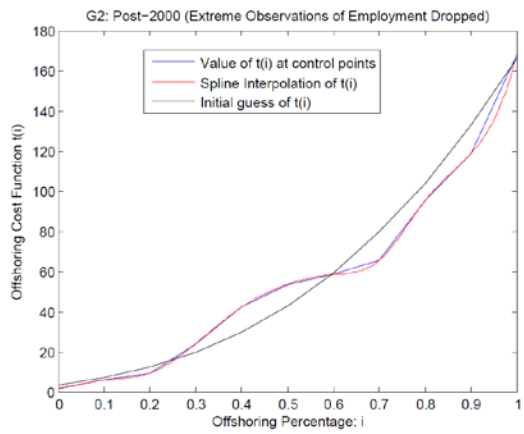


Figure 2: Post-2000 Period (2000-2011)
Offshoring Cost Function for Five Offshorable Occupational Groups

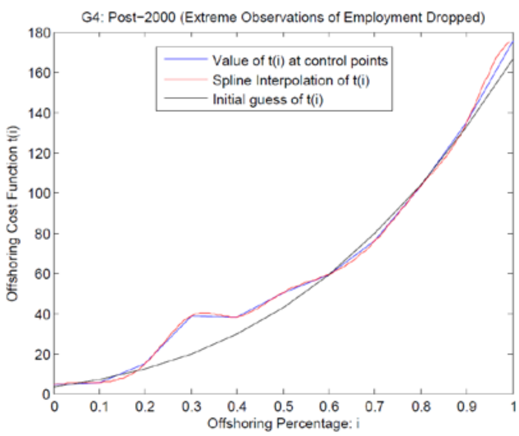
Group 1 (20% Scenario)



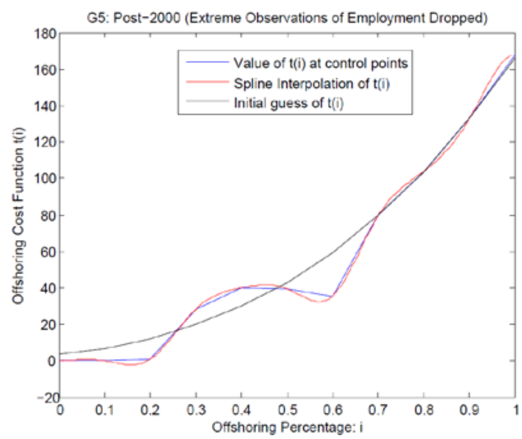
Group 2 (20% Scenario)



Group 4 (20% Scenario)



Group 5 (40% Scenario)



Group 9 (80% Scenario)

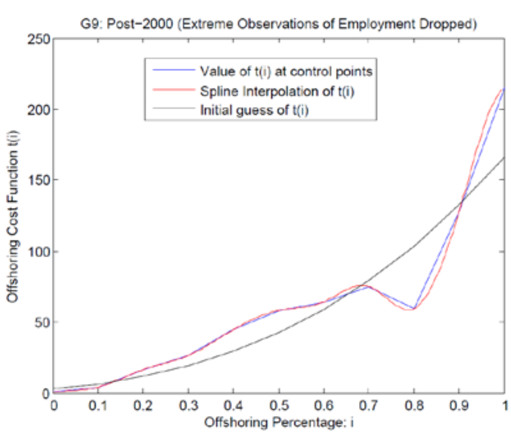


Figure 3: Change of Offshoring Percentage for Five Offshorable Occupational Groups

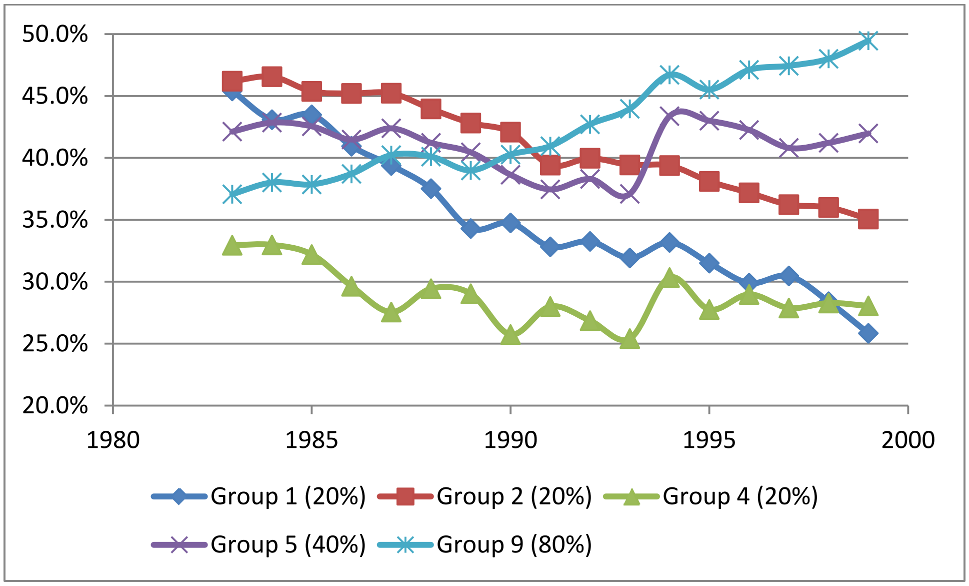


Figure 3.1: Pre-2000 Period (1983-1999)

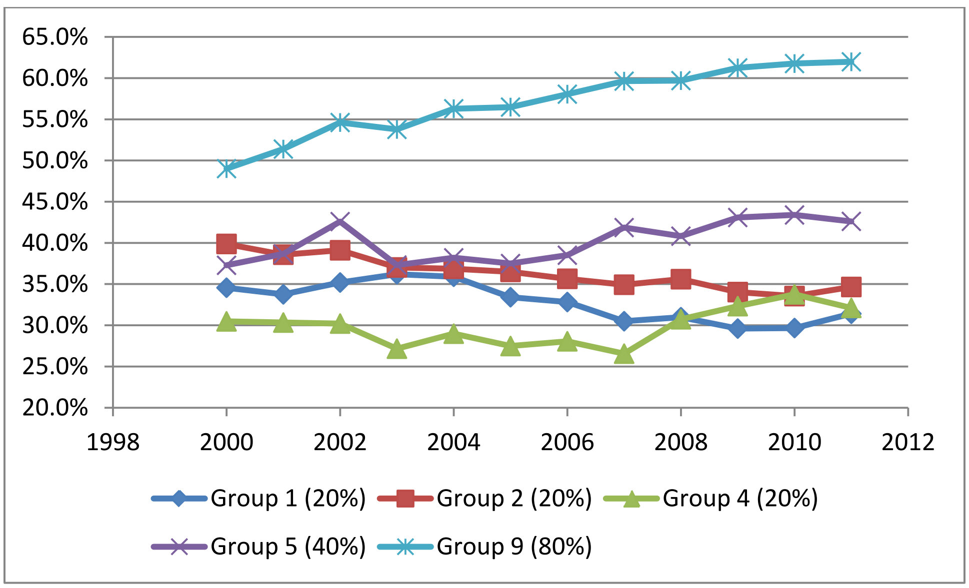


Figure 3.2: Post-2000 Period (2000-2011)