Taking Selection to Task: Bounds on Trends in Occupational Task Prices for the U.S., 1984-2013 [1]

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Abstract

In the large literature on polarization in the wage and employment structure, arguments about shifts in relative demands for different task based groups have been built on comparisons of movements in employment and wages. In particular, increases in both wages and employment in cognitive task occupations relative to routine task occupations are the basis for arguments that Information Technology innovations are driving labor market polarization. But movements in average wages by occupation are misleading measures for determining underlying demand forces for two reasons. First, the workforce has undergone substantial compositional changes in terms of education levels, the age distribution, and the gender composition. Second, it seems reasonable to assume that the large shifts in the proportion of workers in different occupations has been accompanied by shifts in composition in terms of unobservable task related abilities. In this paper, we provide estimates of movements in task prices for the US for the period from 1984 to 2013. To do this, we adjust for changes in observable variable composition and address selection on unobservables through a bounding exercise. We tighten the bounds by appealing to the logic of standard Roy Models. In particular, we derive and implement the bounds associated with different versions of the Roy Model based on different assumptions about the joint distribution of abilities across sectors. We find that task prices for cognitive, routine and manual occupations increased strongly through the 1990s, with some evidence of polarization, but all three declined strongly, and to a similar extent, after 2000.

1. Introduction

A long and growing list of papers characterize labour markets in developed economies as undergoing a polarization of their employment structures and an increase in wage inequality in the last few decades. There are various explanations for these trends but all of them are judged ultimately on how they accord with core patterns in the data. For example, Katz and Murphy (1992)'s claim that the U.S. economy underwent a skill-biased demand shift in the 1980s rested on the observation that both the average wages of the more educated and their employment levels were rising relative to those of the less educated. Many different models of what was happening in the U.S. labour market have emerged since that initial paper but all of them have had to include some element of a shift in relative demand. Similarly, work by David Autor and co-authors has argued that polarization in the U.S. labour market since the early 1990s reflects increased demand for both cognitive and service tasks related directly or indirectly to the computer revolution (Autor, Levy, and Murnane 2003; Autor, Katz, and Kearney 2007; Acemoglu and Autor 2011). Again, the claim that we are witnessing demand shifts of this type is based on that observation both employment and wages for service and cognitive workers increased in the U.S. in the 1990s. Beaudry, Green, and Sand (2012), on the other hand, argue that the 2000s in the U.S. can be characterized, relative to the 1990s, as a period of declining demand for cognitive tasks and a large positive supply shock in the labour market for service workers. Support for this argument, too, comes down ultimately to relative movements in employment rates and wages in the various occupation groups.

Given the way these arguments are built, it is important to get appropriate measures of wage movements for workers of different skill types. This, though, is complicated by two main issues. First, there have been substantial compositional shifts in the workforce coinciding with the increases in inequality and polarization. Both female labour force participation and the average level of education in the U.S. workforce have increased substantially in recent decades, and these have been accompanied by the movement of the baby-boom through the age structure. Any one of these is large enough to affect the average wages we see in the economy; together they form a compositional tidal wave.

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The second issue is indicated by the economic models used to interpret changes in the wage structure. In models addressing polarization patterns, in particular, workers must be allocated to different sectors in the economy. By far the most common approach taken in these models is to incorporate some version of a Roy model in which workers have heterogeneous abilities in the various sectors and each worker chooses a sector to maximize his or her earnings. More specifically, workers are endowed with a vector of abilities corresponding to the various tasks demanded in each sector. The combination of firm demand for labour and the supply decisions of workers determines a price for each of these tasks in equilibrium. The wage a worker would get in a sector then reflects a combination of his or her abilities in the tasks specific to that sector and the task prices in the economy. If demand for the tasks in one sector increases (as, for example, is argued to have happened for cognitive sector tasks as a result of computerization) then the price for tasks in that sector will increase but movements in the observed average wage in the sector are less clear. This is true because the increased task price will draw more workers into the sector and, in a classic Roy model, those new workers will have lower average task abilities in that sector than those who were already working there. Thus, the average observed wage will be affected by offsetting effects in the form of an increased task price but a declining average ability of workers in the sector. In this context, what is needed for evaluating the competing models of changes in the labour market is task prices not average wages. It is these prices that reflect the deeper forces in terms of shifts in production technology, etc., in which we are interested. Our goal in this paper is to provide estimates of trends in task prices that could prove useful in helping to adjudicate among the various models of polarization in particular and wage trends more generally.

The idea that wages need to be adjusted for shifts in observable and unobservable characteristics is not a new one. A considerable literature exists that assesses the importance of compositional shifts over the business cycle in order to establish whether the actual price of labour moves cyclically or counter-cyclically (e.g., Solon, Barsky, and Parker (1994)) We follow that literature in the way we address shifts in composition in terms of observable characteristics.

The idea that it is task prices, rather than wages, that are the relevant construct is also not new; going back, in a Roy model context, at least to the work of Willis and Rosen (1979) and Heckman (1979) in the late 1970s and, at least implicitly, back as far as the Roy (1951) model itself. More recently, Acemoglu and Autor (2011) raised the point in the context of the recent polarization literature. Yet, in spite of the models of polarization being about the shifting of workers across sectors, we know of only two other papers that have attempted to address the impact of composition and selectivity on wages (or, in other words, to get the task prices) in this context: Cortes (2012) and Böhm (2015). We build on those papers by providing new estimates of trends in task prices using a more general approach.

Given that we are interested in providing evidence relevant to analyses of polarization patterns, we divide our data into what has become a commonly used set of sectors in the polarization literature. In particular, we divide occupations into Cognitive, Routine, and Manual occupations, following Acemoglu and Autor (2011), and seek to establish the trends in the task prices associated with each of these occupation groups. We begin by using a standard shift-share analysis in order to control for the effects of composition in terms of observable characteristics on observed wage patterns. We show that moving from using unconditional median wages within sectors to adjusting for education, age and gender composition has substantial impacts on the trend in the central tendencies of the wage distributions in each of the three sectors. The importance of shifts in observable characteristics may point to substantial impacts from selectivity in terms of unobservable abilities, as well. One possible approach to cutting through selectivity effects is to use a Heckman-correction for selection in sector specific wage regressions. However, the believability of the results from such an exercise rests on the validity of functional form assumptions or exclusion restrictions in the form of variables that affect sector selection but do not enter the wage determination process directly. Bohm(2015) can be read as a control function type approach in this spirit and, like all such papers, requires strong assumptions on what determines wages versus selection. We do not have good candidates for such exclusion restrictions and so do not pursue this approach.

A second candidate for obtaining task prices is the one pursued in Cortes (2012). This approach, which has also been used in the cyclical wage movements literature, follows individual workers using panel data. The idea is that if a worker's task specific abilities do not change over time then within-sector changes in that worker's wage over time must reflect changes in the sectoral task price. While this is a potentially promising approach, its usefulness is challenged by the results from the literature that establishes that implicit contracting models and other models with wages that are sticky within jobs are useful lenses through which to examine the labour market (Beaudry and DiNardo 1995, for example). The results in that literature indicate that movements in the wages of higher tenure workers reflect contracting issues that divorce them from movements in contemporaneous productivity changes and the task price movements that are based on them. Given these arguments, we work with wages for new job entrants, which we see as better capturing contemporaneous task price changes.

Working with new entrants solves potential problems related to the stickiness of wages for workers within a firm over time but it does not address the problem of selection on unobservables that arises because successive cohorts of new entrants face potentially different task prices and make different occupation choices as a consequence. To address the selection problem, we form bounds on the movements in task prices using an approach that is in the spirit of Manski (1990) and Horowitz and Manski (2014), and motivated by recent papers by Lee (2009) and Blundell, Gosling, Ichimura, and Meghir (2007) in other contexts. We seek to tighten the bounds using a minimum amount of economic theory - trying to balance a desire to get well-defined bounds with a desire to provide results that will be seen as useful by researchers investigating a potentially wide variety of driving forces. We believe the Roy model is sufficiently widely used that imposing restrictions based on it strikes the right balance. For the most part, we use the core logic of the model - that individuals choose the sector where they earn the highest expected return - and show that even that basic logic helps in tightening bounds. But there are different versions of the Roy model based on different assumptions about correlations of sectoral ability across sectors and we show how the bounds calculations differ depending on the specific form of the model we use. To the best of our knowledge, this is the first paper to develop an approach for bounding changes in selection adjusted wages and task prices, and we provide conditions under which our approach generates consistent bounds for those changes.

The bounding approach amounts to using combinations of changes in observed wage distributions and changes in sector sizes to generate bounds on true task price movements for each of the Cognitive, Manual and Routine sectors. We find that adjusting for observable composition changes and focusing on wages for new entrants yields wage trends that are similar to what has been described in other papers before 2000, with wages rising for both cognitive and manual occupations and routine wages rising less. But after 2000, while the unconditional median wages continue to rise (albeit much more slowly) for cognitive and manual workers, our adjusted series show substantial declines in these wages. Our counterfactual bounds corresponding to different assumptions about selection on unobservables into the various sectors show that even with extreme assumptions on what ability types are moving into and out of sectors, we continue to see the same pattern: increases in wages in all sectors in the 1990s followed by declines in the 2000s. Indeed, we show that Roy models have stochastic dominance implications that, in turn, imply that the median wage changes based just on holding observables composition constant form one of the extreme bounds. The other bound shows more negative wage movements in all sectors in the 2000s, indicating that the task price declines are at least as large as what is obtained from the standard shift-share exercise.The fact that this conclusion is reflected in bounds based on all the versions of the Roy model we consider indicates that this is a robust pattern. The result that the cognitive sector price falls by a similar magnitude as the other sector prices in the 2000s does not fit with an ongoing skill biased demand shift. The fact that wages in all three sectors fall does match recent observations that the share of labour in total income has been declining and with a general decline in demand for labour (Karabarbounis and Neiman 2013; Elsby, Hobijn, and Åđahin 2013)

The paper proceeds in six sections, including the introduction. In section 2, we set out a basic wage determination and sector selection model. In section 3, we describe how we generate bounds on movements in sectoral task prices under different assumptions about the correlation of sectoral abilities across sectors. In section 4, we discuss data issues, including providing a defense of our focus on the wages of young, new labour market entrants. Section 5 contains our results and section 6 concludes.

2. Theory

2.1. Wage Determination

Our goal in this paper is to present price trends that can be used to distinguish among a wide set of competing models of inequality and polarization. Thus, we want to work with as general a model of wage determination as possible. But we begin with a simple model as a venue for explaining our estimation approach and identification issues. In particular, we will start with a wage determination model in which the only non-stationary component is the price of tasks, there are no covariates, and the log wage equation can be written as additively separable in underlying price and ability components. After our initial discussion, we introduce other time-varying parameters and covariates and will provide a discussion of the assumptions we require on the functional form of the wage equation in order to obtain bounds on changes in task prices.

Consider firms hiring workers who provide one of three types of tasks: C (cognitive); R (routine); and M (manual). We take the tasks to correspond directly to occupations and index the task/occupation type by k. Firms hire workers, indexed by i, with task output generated by a specific worker given by

$$z_{ikt} = \eta_i^{\gamma_k} e^{\nu_{ik}} e^{\epsilon_{ikt}} \tag{1}$$

That is, worker productivity in a task, k, has an idiosyncratic, time varying component, $e^{\epsilon_{ikt}}$ and two time invariant components: an absolute advantage component, η_i, which is applicable across sectors but with differential impacts dictated by the γ_k parameters; and a comparative advantage component, $e^{\nu_{ik}}$. The three components are independent across workers and of each other for the same worker. The $e^{\nu_{ik}}$ component is independent across sectors for a given worker. The idiosyncratic component is drawn from a distribution with $E(e^{\epsilon_{ikt}}) = 1$, and all three components are drawn from stationary distributions. This structure allows for an element of ability that is correlated across sectors (η_i); a component that reflects differential abilities across sectors ($e^{\nu_{ik}}$); and a component that captures elements such as measurement error or short term events that can alter ability and observed wages from period to period.

The value of marginal product of the worker is given by

$$\Phi_{ikt} = p_{kt} z_{ikt}, \tag{2}$$

where p_{kt} is the price of task k. Finally, we assume, for now, that wages are determined in a spot market so that workers receive the value of their marginal product. We will return to a more general discussion of wage determination in section 4 when we describe our choice of wage measure.[2] Given our assumptions so far, the log wage faced by worker i in occupation k in period t is given by:

$$\ln w_{ikt} = \ln p_{kt} + \gamma_k \ln \eta_i + \nu_{ik} + \epsilon_{ikt} \text{ for } k \in \{C, R, M\}, \tag{3}$$

[2] In the appendix, we derive the same wage equation from an implicit contract model with aggregate trends and discuss the implications of that model for the wage measure choice.

2.2. A Roy Model with Three Sectors

We turn, next, to the problem of the allocation of workers to occupational sectors. Following many other papers, we discuss the allocation as determined by individual choice in the context of a Roy model. We consider the problem of an unemployed person choosing among the three sectors, C,R, and M, abstracting from the possibility of workers currently employed in a sector deciding whether to remain in that sector or move to another. A person chooses the sector in which to work based on a comparison of the present value of expected wages plus other sector-specific, work related costs. To simplify the exposition, we focus on a case in which p_t has a stochastic trend (i.e., $p_{kt} = p_{kt-1} + \xi_{kt}$ with ξ_{kt} being a disturbance that is independent across sectors and time) and the ϵ_{kit} ability component is unforecastable by the worker (such as would be the case if it just corresponds to measurement error).[3] In this case, an individual chooses a sector based on a comparison of the sector's current wages and costs. Thus, a person prefers sector C to sector R *iff*:

$$\ln w_{iCt} - u_{iCt} > \ln w_{iRt} - u_{iRt}, \tag{4}$$

where u_{ikt} is an idiosyncratic cost of working in sector k and is assumed to be independent of all the ability components. Substituting from (3), we can re-arrange (4) as:

$$Z_{iCRt} = (\gamma_C - \gamma_R) \ln \eta_i + \nu_{iC} - \nu_{iR} - (\ln p_{Rt} - \ln p_{Ct}) + \varepsilon_{iCRt}, \tag{5}$$

where $\varepsilon_{iCRt} = \epsilon_{iCt} - \epsilon_{iRt} - u_{iCt} + u_{iRt}$ and person i prefers sector C to sector R *iff* $Z_{iCRt} > 0$ and prefers sector R to sector C otherwise. Similar equations can be written for comparing sector C to sector M, and for comparing sector M to sector R.

3. Addressing Selection Using Bounding

Given our wage specification and the sector selection mechanism, we can write the median log wage for workers observed to be working in sector C, as:

$$\text{Med}\left[\ln w_{iCt} | Z_{iCRt} > 0, Z_{iCMt} > 0\right] = \ln p_{Ct} + \text{Med}\left[\gamma_C \ln \eta_i + \nu_{iC} + \epsilon_{iCt} | Z_{iCRt} > 0, Z_{iCMt} > 0\right], \tag{6}$$

with parallel expressions existing for observed median log wages in the other two sectors. Our goal is to identify changes in the task prices since they reflect the underlying demand and supply forces that affect the labour market. Task prices are not directly observable and so researchers work with their closest analogue: sector specific mean or median wages. However, inspection of (6) indicates that changes in the median observed wage in a sector will reflect both changes in the task price and shifts in the composition of those working in the sector. In fact, the indexes that determine whether

[3]The conclusions would be the same but the exposition more complicated if we allowed for p_{kt} and e_{ikt} to be forecastable.

a person works in a specific sector (the z's) are functions of the relative task prices and, as we will discuss later, an increase in the task price in a sector relative to those in the other sectors draws in new workers who are, on average, less able than those already in the sector. As a result, a task price change generates an offsetting selection effect that implies that observed wage movements are a potentially poor reflection of task price movements. Thus, to obtain estimates of changes in task prices we need to address coincident changes in worker selection across sectors.

One potential method for addressing the selection issue is to use a variant of a Heckman two-step approach to estimate selection corrected wage regressions. In principle, using distributional assumptions and/or exclusion restrictions, one could identify all of the parameters in the wage determination model, including the sector specific prices French and Taber (2011). However, we do not have a plausible set of exclusion restrictions among the variables in our data and so, instead, address the selection issue using an approach that is in the spirit of the Blundell et al. (2007) and Lee (2009) and involves bounding the price movements. While this bounding can be done using purely statistical arguments, we attempt to provide sharper bounds by employing a minimal amount of theory embodied in the Roy-type selection model just described. As we will see, the specifics of the bounding will depend crucially on assumptions about the error terms in equations (3) and (5). We consider a set of specific cases that correspond to the Roy model sub-cases described in Willis (1986). We begin with the most straightforward case: an hierarchical ability model with three sectors and no observable covariates. In that model, there is one ability factor that is common across sectors so that Michael Jordan would not only be the best basketball player but also the best golfer, the best lawyer, the best carpenter, etc.. This is clearly unrealistic but this simple form for wage determination will allow us to establish the main intuition and mechanics of our approach in a straightforward (and commonly used) context. We then discuss the addition of covariates and a fourth sector (non-employment) as well as allowing for wage determination parameters to vary over time before moving to a more heuristic discussion of implications of other ability structures. In particular, we will consider an Independent Shocks model in which individual abilities are completely independent across sectors (so that knowing that Michael Jordan is the best basketball player tells us nothing about how able he would be in other sectors) and a Combination model that allows both for a common ability factor that is productive in all sectors and independent, sector specific abilities.

3.1. Hierarchical Ability Model

The first (Hierarchical Ability) model is one of the most commonly used in analyses of this problem. For example, it is the model that implicitly underlies many discussions of returns to education. In this model, we assume that there is only one type of ability affecting wages and sector choice, but allow it to be differentially productive in generating task units in each sector. That is, assume that worker productivity given in (1) can be simplified to:

$$z_{ikt} = \eta_i^{\gamma_k} e^{\epsilon_{ikt}}, \tag{7}$$

which assumes that there is no comparative advantage ability component. We also assume that the ϵ_{ikt}'s correspond to classical measurement error or some unforecastable shocks that only temporarily shift wages and, so, do not enter the sectoral choice processes. Finally, there are no idiosyncratic costs (u_{ikt}'s) in the selection process.[4] Given these assumptions, the wage equation becomes:

$$\ln w_{ikt} = \ln p_{kt} + \gamma_k \ln \eta_i + \epsilon_{ikt} \text{ for } k \in \{C, R, M\} \tag{8}$$

and the equation determining preference of sector C over sector R becomes:

$$Z_{CRit} = (\gamma_C - \gamma_R) \ln \eta_i - (\ln p_{Rt} - \ln p_{Ct}). \tag{9}$$

We continue to maintain the assumptions on independence and stationarity of the distributions for the η_i and ϵ_{ikt} components described earlier.

We follow Blundell et al. (2007) in focusing on estimation of median wages because, as we will see, this provides a natural way of using the implications of the selection model and allows us to employ weaker assumptions about where in the ability distribution sector joiners and leavers come from. To begin, we can write the median log wage in the C sector as:[5]

$$\text{Med}\left[\ln w_{iCt} | Z_{iCRt} > 0, Z_{iCMt} > 0\right] = \ln p_{Ct} + \text{Med}\left[\gamma_C \ln \eta_i + \epsilon_{iCt} | \ln \eta_i > A_{CRt}, \ln \eta_i > A_{CMt}\right], \tag{10}$$

where $A_{CRt} = \frac{(\ln p_{Rt} - \ln p_{Ct})}{(\gamma_C - \gamma_R)}$ and A_{CSt} is defined analogously. Capital letters correspond to random variables and small letters correspond to specific realizations of those random variables. As Cortes (2012) shows, under a natural ordering of the factor loadings ($\gamma_C > \gamma_R > \gamma_M$) and an associated set of prices, A_{CRt} corresponds to a threshold value for $\ln \eta_i$ such that individuals with $\ln \eta_i > A_{CRt}$ work in the C sector; individuals with $\ln \eta_i \leq A_{CRt}$ and above another threshold work in the R sector. Given this, only one of the inequalities in (10) binds and we can re-write it as:

$$\text{Med}\left[\ln w_{iCt} | Z_{iCRt} > 0\right] = \ln p_{Ct} + \text{Med}\left[\gamma_C \ln \eta_i + \epsilon_{iCt} | \ln \eta_i > A_{CRt}\right]. \tag{11}$$

To understand the bounding approach to the selection issues, it is useful to write out the expression that implicitly defines the median log wage in sector C in time t (11), which we will call m_{Ct} as:

$$\Pr(\ln w_{iCt} < m_{Ct} | \ln \eta_i > A_{CRt}) = 0.5. \tag{12}$$

Next, assume there has been an increase in ($\ln p_{Ct}$ - $\ln p_{Rt}$). Under the standard selection model set out earlier, such a price change implies that some workers will move into C but none will move out. Because of this, we can write:

$$\begin{aligned}\Pr(\ln w_{iCt+1} < \tilde{m}_{Ct+1} | \ln \eta_i > A_{CRt+1}) &= \pi_{Ct+1} \Pr(\ln w_{iCt+1} < \tilde{m}_{Ct+1} | \ln \eta_i > A_{CRt}) \\ &+ (1 - \pi_{Ct+1}) \Pr(\ln w_{iCt+1} < \tilde{m}_{Ct+1} | A_{CRt} \geq \ln \eta_i > A_{CRt+1}),\end{aligned} \tag{13}$$

[4] Excluding these cost shocks simplifies the exposition. Assuming they are independent of the ability factors, including the cost shocks does not alter the conclusions in this section.

[5] Median wages in the other sectors have analogous expressions.

where (1 -π_{Ct+1}) is the proportion of people in C in period $t+1$ who entered C because of the price change and $\tilde{m}_{Ct+1}$ is the median log wage in $t+1$ for the workers who would have been in sector C under period t prices. That is, $\tilde{m}_{Ct+1}$ is defined by:

$$\Pr(\ln w_{iCt+1} < \tilde{m}_{Ct+1} | \ln \eta_i > A_{CRt}) = 0.5 \tag{14}$$

and can be written as:

$$\tilde{m}_{Ct+1} = \ln p_{Ct+1} + \text{Med}\left[\gamma_C \ln \eta_i + \epsilon_{iCt+1} | \ln \eta_i > A_{CRt}\right]. \tag{15}$$

If we could get an estimate of $\tilde{m}_{Ct+1}$ then subtracting (11) from (15) would provide an estimate of the change in the C sector task price.[6] In fact, we provide bounds for this change. We call the set of people in the conditioning set in these equations the "stayers," or "always-takers" *i.e.*, the set of people who would choose sector C under prices in either period. Similarly, we will call the set of people who would choose one sector under the period t prices and another sector under the period $t+1$ prices "movers" or "compliers."[7]

To generate bounds, return to (13) and note that the probability on the left hand side is based on a distribution we observe (the C sector wage distribution for workers observed in the sector in $t+1$). Under the selection model assumptions, we also know that an increase in the relative price of the C task will imply an inflow of people from sector R to C but no flows out of C. Thus, we can get π_{Ct+1} as the change in the number of people in sector C divided by the total number of people in sector C in period $t+1$. This leaves two probabilities on the right hand side of (13) that are unknown. Under the bounding approach, we adopt extreme values for one of these probabilities in order to bound the possible values of the other. In our case, since we are interested in the median wage for the "stayers," we will form bounds on it by adopting extreme values for the the probability associated with the "movers" (workers with η_i values such that they would choose sector R in period t but would choose sector C in response to the price increase in period $t+1$). It is not important for our purposes to identify the extent of selection by identifying the differences in ability between the two groups. All we need is to follow observed median wages over time (or bound median wage changes over time) for an ability constant set of workers. We focus on the stayers for that purpose.

The widest bounds we can form on the changes in median C wages for the sector stayers are associated with the fact that $\Pr(\ln w_{iCt+1} < \tilde{m}_{Ct+1} | A_{CRt} \geq \ln \eta_i > A_{CRt+1})$ is a probability and

[6] This statement is true if $\text{Med}\left[\ln \eta_i + \epsilon_{iCt}\right] = \text{Med}\left[\ln \eta_i + \epsilon_{iCt+1}\right]$ which holds if, as we have assumed, $\epsilon_{C\tau}$ is drawn from a distribution that is stationary over time.

[7] In section 4, we argue for tracking task price movements by following the cross-cohort movements of wages of new labour force entrants. In that context, the term "stayer" doesn't strictly apply. Instead, given the stationarity of the η_i distribution, it refers to people with the same set of values for η_i in each period, and "movers" are people with values of η_i that would cause them to select the C sector in the second period but not under the lower, first period relative price.

so must lie between 0 and 1. In particular, if this probability equals zero then we are making the extreme assumption that all movers have abilities such that their wages are above the median wage for stayers, and we can write:

$$\Pr[\ln w_{iCt+1} < \tilde{m}_{Ct+1} | \ln \eta_i > A_{RCt}] \leq \frac{1}{\pi_{Ct+1}} \Pr[\ln w_{iCt+1} < \tilde{m}_{Ct+1} | \ln \eta_i > A_{RCt+1}] \tag{16}$$

and, if it equals 1 then we are assuming that all movers have wages below the median wage for stayers and we obtain,

$$\begin{aligned} \Pr[\ln w_{iCt+1} < \tilde{m}_{Ct+1} | \ln \eta_i > A_{RCt}] > \frac{1}{\pi_{Ct+1}} & \Pr[\ln w_{iCt+1} < \tilde{m}_{Ct+1} | \ln \eta_i > A_{RCt+1}] \\ & - \frac{(1 - \pi_{Ct+1})}{\pi_{Ct+1}}. \end{aligned} \tag{17}$$

Then setting the left hand sides of (16) and (17) to 0.5 (since that defines $\tilde{m}_{Ct+1}$), and solving them as equalities yields estimates of the lower bound on $\tilde{m}_{Ct+1}$, $\tilde{m}^L_{Ct+1}$, and the upper bound, $\tilde{m}^U_{Ct+1}$, respectively. Once we have these, we can form a lower bound on the increase in the sector C task price as ($\tilde{m}^L_{Ct+1}$ - m_{Ct}) and an upper bound as, ($\tilde{m}^U_{Ct+1}$ - m_{Ct}). One can show that the solutions to (16) and (17) are the equivalent of trimming π_{t+1} proportion of observations from the top and bottom of the period $t+1$ C sector wage distribution, respectively, and then obtaining medians for these trimmed distributions.[8] This is similar to the implementation in Lee (2009) and is the way we obtain the bounds. We will call the bounds formed in this way (trimming from either the top or the bottom of the distribution) the Extreme Bounds. We will describe ways of using economic theory to tighten the bounds as we proceed but it is worth pointing out that even the minimal amount of economic structure we have used so far has already helped narrow potential bounds. In particular, if workers both enter and leave the C sector in response to a relative price increase then one would want to trim from both the period t and $t+1$ distributions and almost any trend could likely be supported. But with the standard index based selection model workers will move only in one direction in response to a price change and we can get wage movements for the stayers by trimming only the $t+1$ distribution since all the people in the period t distribution are stayers.

We derived the formulae for the bounds assuming that the relative price of C had increased. If, instead, it had decreased then workers would exit sector C between periods t and $t+1$. In that case, we would form bounds by trimming a number of workers equivalent to the net decrease in the size of the C sector from the top and bottom of the period t distribution of C sector wages and comparing the medians of the resulting distributions to the median wage for all workers in sector C in period $t+1$. Given the logic of the model, we can determine which type of trimming to do based

[8]Note that because we are working with medians, we only need to assume that all the sector joiners enter below the median, not that they enter at the extreme lower end of the distribution.

on the sign of the net change in the number of workers in C.[9] That is, if we observe a net increase in the number of workers in C between two periods then we know there must have been a relative increase in the price of C tasks and we trim from the period $t+1$ distribution, accordingly. If we observe a net decrease in number of workers in C then we form bounds by trimming the period t distribution.

3.1.1. Generating Bounds for the R and M Sectors

The approach just outlined for generating bounds for the C sector task prices can be used in a similar manner to construct bounds for the R and M sector prices. For the M sector, in fact, the approach is identical. If the size of the M sector expands this implies that $\ln p_{Mt}$ has increased relative to $\ln p_{Rt}$ (recalling that with the single factor ability model, workers moving in or out of M are only moving from and to the R sector). As with the C sector analysis, bounds can then be formed by trimming the number of workers equal to the net change from either the top or the bottom of the M wage distribution in period $t+1$ and obtaining medians of the trimmed sample. If M declines in size then, again as with the C sector, the trimming would be done on the period t sample.

For the R sector, the analysis is somewhat more complicated because changes in $\ln p_{Rt}$ have to be compared to movements in both $\ln p_{Ct}$ and $\ln p_{Mt}$. This does not cause problems if $\ln p_{Rt}$ increases with respect to both of the other prices or decreases with respect to both. In either case, the change in the number of workers in the R sector can be used to trim distributions and form bounds in the same way as just described for the other two sectors. However, if $\ln p_{Rt}$ rises relative to the task price in one sector but falls relative to the task price in the other sector then there will be both flows in and out of the R sector. In that case, the net change in the size of the R sector is not informative for forming bounds. Fortunately, within the context of the single ability model we know the size of the gross flows into and out of the R sector. In particular, both the changes in the number of workers in C and the change in the number of workers in M must imply equal and opposite changes in the numbers in R since there are no flows between the M and C sectors. Suppose, then, that N_{RCt} $(= \Delta N_{Ct})$ workers move from R to C and N_{MRt} $(=|\Delta N_{Mt}|)$ move from M to R. We can form an upper bound on the movement in the median wage for sector R stayers (and with it, given the wage determination model set out in the previous section, the movement in the price in R) by trimming N_{RCt} observations from the top of the period t R sector wage distribution and trimming N_{MRt} observations from the bottom of the period $t+1$ R sector wage distribution. We then get the medians from each of the trimmed samples and take the difference between those medians. The lower bound would be obtained by trimming N_{RCt} observations from

[9] Note that we could allow for gross flows in both directions between sectors in the model by including exogenous shocks reflecting, for example, whether a close friend had joined a specific sector. If these shocks are independent of price movements then the net flows will reflect the responses to the price changes that are of interest to us.

the bottom of the period t R sector wage distribution and N_{MRt} from the top of the period $t+1$ distribution.

3.1.2. Identifying Assumptions

The procedure in the previous subsection identifies bounds on movements in a composition constant median wage if two conditions are met:

1. Monotonicity. A non-randomly selected (with respect to η) set of workers can be added to or withdrawn from a sector in a period, but both cannot happen at the same time.
2. Time invariance of the η distribution, i.e., $F_t(\eta) = F(\eta)$

Under the Monotonicity assumption, the observed change in the proportion of workers in the C sector corresponds to the entire relevant movement in workers into or out of the sector and allows us to use that proportion to form bounds. If, instead, non-random selections of workers both entered and left the sector at the same time then trimming according to the net change will not result in a composition constant set of workers. The basic selection model, in fact, imposes the monotonicity assumption: people will only move one way or the other in response to a price change or a change in the cost of entering the sector given the linear index determining the sector the person is in. This is a key point from Vytlacil (2002), which demonstrates formally that standard selection models are equivalent to imposing monotonicity.[10]

The time invariance assumption says that the overall distribution of abilities in the population does not change and, so, the distribution of abilities in a sector changes only because of worker movements in response to price or cost changes; movements that we address using the bounding approach. Without this assumption, trimming the number of workers added to the sector between period t and $t+1$ will not result in a trimmed period $t+1$ sample with the same ability distribution as the period t sample and we would not have formed bounds on a composition constant median wage.[11] As a specific instance of this assumption, it requires that changes in the task prices do not induce changes in the ability distribution, i.e., $f(\eta|p_{kt}) = f(\eta)$. Such a change could arise if workers obtained sector specific training in response to the price changes, and so we must assume away such responses.

[10] As described earlier, there can be random movements of workers both in and out of the sector. We just require the movements induced by the price or cost changes to satisfy Monotonicity in order to identify task price changes since it is movements that alter the ability composition in the sector that are of concern to us.

[11] Increases in the number of university educated workers over time has the potential to generate a violation of this assumption, even if we focus just on one education group. The time invariance assumption would require that any new additions to the education group are random draws from the same ability distribution as those already in the education group. We address this explicitly in our discussion of covariates and observable skill groups in section 3.1.5.

Under these two assumptions, changes in the median and all other percentiles for a composition constant set of individuals are identified. Like other just-identification assumptions, these assumptions cannot be tested.

Our approach can be seen as an application of the approaches in Blundell et al. (2007) and Lee (2009), which are themselves built on the work in Manski (1990). Blundell et al. (2007) obtains bounds on the median wage unconditional on working, addressing the problem that workers are not selected randomly. This would be equivalent to our bounding the median wage that would hold if all workers were employed in one sector. Since we are ultimately interested in bounding changes in task prices, we only require a bound on movements in wages for some composition constant subset of workers. This is the approach in Lee (2009) and the one we follow here.[12] It provides bounds that are less erratic than those on the unconditional median obtained under the Blundell et al. (2007) approach. Indeed, bounds on the unconditional median wage in a sector often do not exist if the size of the sector is sufficiently small. In particular, if the sector contains less than 50% of the workforce then it is not possible to bound the wage for the median person in the whole workforce.

The main difference between our work and the existing literature is that previous papers bound the median or mean wage. We want to identify not just wage movements but the movements in the task prices that underlie these wage changes. This requires a second set of assumptions under which we can obtain the price changes from the changes in the composition constant median wage movements. To understand those assumptions, it is useful to move away from our original additively separable wage specification, writing the wage determination equation in a more general form:

$$w^*_{ikt} = f_k(x_{it}, \eta_{ik}, p_{kt}, \epsilon_{ikt}; \theta_t) \tag{18}$$

where: x_{it} is a vector of potentially time varying observable covariates; $\eta_{ik}, p_{kt}, \epsilon_{ikt}$ are unobservable covariates; and θ_t is a vector of parameters that may be time varying, including γ_{kt} in the earlier specification. For the moment, assume that we stratify on the x_{it} vector and so ignore that part of the function. We return to considering covariates in the next section. Our objective here is to ascertain the minimal set of restrictions on $f_k(\cdot)$ that would allow us to argue that movements in the composition constant median wage reveal movements in the underlying task prices.

Leaving aside covariates, two main issues arise in determining the wage functions that can be used to identify the change in sector prices. The first relates to other time varying arguments in $f_k(x_{it}, \eta_{ik}, p_{kt}, \epsilon_{ikt}; \theta_t)$. If, in particular, any of the parameters defining the $f_k(\cdot)$ function are time varying then changes in the median wage will, in part, reflect changes in those parameters. For example, in the simple additively separable wage specification that we have used so far, if the sector specific factor loadings on ability (the γ_k's) are time varying then the change in the median log wage will equal $\Delta p_{kt} + \Delta \text{Med}\left[\gamma_{kt}\eta_i + \epsilon_{ikt} | \eta_i > A_{CRt}\right]$. Thus, changes in the median wage, $\tilde{m}(w^*)$, could be driven by either or both of changes in p_{kt} or γ_{kt}. In other words, the two forces are not separately identified.

[12] Our identifying assumptions are re-statements of those in Lee (2009).

One potential response to this problem is to impose an assumption that restricts $\theta_t = \theta$. However, we can separately identify movements in p_{kt} and time-varying components of θ_t under the assumption that $f_k(\cdot)$ is additively separable as follows:

$$w^*_{ikt} = f_{k1}(x_{it}, p_{kt}; \theta_1) + f_{k2}(x_{it}, \eta_{ik}, \epsilon_{ikt}; \theta_{2t}), \tag{19}$$

where θ_1 contains only time invariant elements of θ and any time-varying elements are contained in θ_{2t}. The key features of this formulation are that $f_{k1}(\cdot)$ contains only p_{kt} and observable covariates while $f_{k2}(\cdot)$ is a non-additively separable function of η_{ik} and θ_{2t}. Our earlier log wage specification follows this form, with θ_{2t} including γ_{kt}. With a wage function of this form, we can identify movements in θ_{2t} through movements in higher moments. In particular, in this formulation a change in p_{kt} will change all quantiles of the wage distribution in the same way (i.e., it only affects the location of the distribution conditional on x). In contrast, since θ_{2t} interacts with η_{ik} in the second sub-function, changes in θ_{2t} will alter the higher moments of the log wage distribution.

To take advantage of this, note that the bounding procedure we have described can be applied to any quantile (not just the median). Working with our earlier expression for log wages, we can write the inter-quartile difference for the log wage in sector C in period t as:

$$\ln p_{Ct} + q3[\gamma_{Ct} \ln \eta_i + \epsilon_{iCt} | \ln \eta_i > A_{CRt}] - \ln p_{Ct} + q1[\gamma_{Ct} \ln \eta_i + \epsilon_{iCt} | \ln \eta_i > A_{iCRt}], \tag{20}$$

$$= q3[\gamma_{ct} \ln \eta_i + \epsilon_{iCt} | \ln \eta_i > A_{CRt}] - q1[\gamma_{ct} \ln \eta_i + \epsilon_{iCt} | \ln \eta_i > A_{CRt}]$$

where $q1[\cdot]$ and $q3[\cdot]$ refer to the first and third quartiles of a distribution, respectively.

Then, using trimming as before, we can generate a difference for period $t+1$ as:

$$(q3[\gamma_{ct+1} \ln \eta_i + \epsilon_{iCt+1} | \ln \eta_i > A_{CRt}] - q1[\gamma_{ct+1} \ln \eta_i + \epsilon_{iCt+1} | \ln \eta_i > A_{CRt}]). \tag{21}$$

Subtracting (20) from (21) provides a bound on the change in γ_{Ct}, identified up to a factor of proportionality. The bound on the change in γ_{kt}, in turn, can be used to adjust our interpretation of the bounds on the movements in the composition adjusted median wage. If the trend in γ_{kt} is flat (i.e., if there are no significant changes in the inter-quartile range of log wages within a sector) then $\Delta\gamma_{kt+1} = 0$ and changes in the median wage identify changes in p_{kt}. If, instead, γ_{kt} follows a discernible trend that is the opposite to the trend in the median wage then we can conclude that the trend in p_{kt} is in the same direction as the trend in the median wage and at least as large as the median wage trend. However, if trends in both γ_{kt} and the median wage are in the same direction then we will be unsure of the extent or direction of any trends in p_{kt}.

One component of the wage function that is unavoidably time varying is e_{ikt}. However, if we assume that its distribution does not vary with t then it does not raise any further problems. In our simple log wage specification, this disturbance enters in an additively separable way, but we could allow for interactions with time varying components of θ. In that case, it would simply be a contributor to the movements in higher moments of the wage distribution just discussed.

The second identification issue is with the function of p_{kt}, $f_{k1}(\cdot)$. If p_{kt} enters the wage determination function through a monotonically increasing transformation then we can bound the direction of the price change but not the magnitude. If it enters through more general functions then even the direction may not be identifiable. To get the magnitude of the price change as well as its direction, we need to assume that p_{kt} enters in a simple linear (or log-linear) fashion with a coefficient of 1, as is the case in our additively separable specification.

In summary, in our initial log linear wage specification, with the factor loadings on ability being time invariant, changes in the composition constant sectoral median wages identify the direction and magnitude of changes in p_{kt}. Allowing for more general functions of p_{kt} and for other time-varying elements of the wage determination function can still permit identification of bounds on, at least, the direction of the trend in p_{kt} under specific assumptions about additive separability and the reasonable assumption that wages are monotonically increasing in task prices.

Finally, it is important to notice that we do not require exogeneity of the price changes in the sense of their not being jointly determined with the supplies of labour to sectors. We are not trying to provide bounds on either supply or demand elasticities but rather to provide bounds on selection-free reduced form price changes that emerge from the operation of the economy. For example, if there were a decline in the cost of entering the C sector then we would observe an increase in the number of C sector workers and the equilibrium price, p_{Ct} would decline. Our goal is to bound that movement in p_{Ct}, addressing the change in the composition of C sector workers that accompanies the change in the size of the sector. Bounding those equilibrium price changes narrows the relevant set of models of the determination of the price changes that can be said to be consistent with the data.

3.1.3. Tightening the Bounds using Stochastic Dominance

We now move to tightening the bounds while working within the Hierarchical model. As Blundell et al. (2007) show, knowing that one of the unobserved distributions stochastically dominates the other can help in tightening bounds. In our case, the logic of the model does imply such a condition. Consider, in particular, sector C wages when the relative price of tasks in C is rising. In that case, it is simple to show that the wage distribution of the stayers first order stochastically dominates that of the people who move into sector C in period $t+1$. That is:

$$\Pr(\ln w_{iCt+1} < x | A_{CRt} \geq \ln \eta_i > A_{CRt+1}) > \Pr(\ln w_{iCt+1} < x | \ln \eta_i > A_{CRt}). \qquad (22)$$

The intuition for this is straightforward and, as we will see, carries over to versions of the Roy model with other ability patterns. Those who are drawn into a sector by an increase in its relative price must be of lower ability than those already in the sector since the latter had such high sector specific abilities that they were willing to choose the sector even when its price was lower. Thus, the stochastic dominance assumption ultimately rests on the assumption that people are voluntarily choosing their sectors in response to price or cost changes.

We can use (22), replacing x with $\tilde{m}_{Ct+1}$, instead of using the bound defined by $\Pr(\ln w_{iCt+1} < \tilde{m}_{Ct+1}|A_{CRt} \geq \ln \eta_i > A_{CRt+1}) > 0$. Using this new bound with equation (13), implies that the new lower bound is $\Pr(\ln w_{iCt+1} < \tilde{m}_{Ct+1}|\ln \eta_i > A_{CRt+1})$, *i.e.*, the actual observed median wage in sector C in period $t+1$. Thus, the lower bound on price changes is just the observed change in median wages in sector C. Intuitively, under stochastic dominance, the best the new sector joiners can be is as good as the stayers and if they were that good then the observed distribution in $t+1$ would be the same as the stayer's distribution. Bounds for the change in $\ln p_{Ct}$ when people are leaving the sector are formed analogously. Sector M can also be solved analogously, with the key exception that now the people moving into the sector have wages that stochastically dominate the incumbents. The operations for dealing with R occupation are, again, more complicated, due to the fact that there can be worker flows to and from both the M and C sectors. However, the structure of the model implies that entrants into R from C have wages that stochastically dominate stayers, and stayers' wages, in turn, stochastically dominate entrants from M. This logic implies the lower bound on price changes is, again, just the observed price change in the R sector.

3.1.4. Introducing Nonemployment

The results so far can easily be extended to a case with nonemployment. Doing this is useful because it allows us to incorporate directly the large increase in female labour force participation in the first half of our sample period and the decline in employment rates for both males and females after 2000 . To do this, assume that there is a fourth sector, H, or home. We do not observe any measure related to the price in this sector and so are only interested in it to the extent it affects wages in the other sectors. In the Hierarchical model, we assume that it fits in below the M sector, *i.e.*, there will be a cut-off, A_{HMt} such that people with η values below this cut-off will be in the home sector.

There are two adjustments we need to make in the model set out above. First, the M sector is no longer an extreme end sector. Instead, it will be treated as the R sector was previously. Second, we need to get values for the flows between H and M, and use them to get values for the flows between M and R (the latter were just the changes in the size of M previously). Under the structure of the model, any change in the number in H (*i.e.*, the number nonemployed) will be the negative of the flows from H to M,*i.e.*, $\Delta N_{Ht} = -N_{HMt}$, where N_{HMt} is the number flowing from H to M. Using this, we then back out the number flowing from M to R as, $N_{MSR} = \Delta N_{Mt} - N_{HMt}$. Once we have these numbers, the bounds for both M and R are constructed in the same way as the bounds for R alone were constructed in the three sector case. Nothing changes for the C sector.

3.1.5. Introducing Covariates

Next, consider the possibility that the characteristics affecting productivity can be divided into ones that are observed and ones that are unobserved. In particular, we assume that the common ability factor can be broken down into an unobserved component, η^*_{ik}, and a component determined by observed variables such as age and education that are elements of a vector x_i. That is, we will assume that worker productivity in task k is given by, $z_{ikt} = \eta_i^{\gamma_k} e^{x_i\beta} e^{\nu_{ik}} e^{\epsilon_{ikt}}$. Based on this, the median wage in sector C under the assumptions for the hierarchical model would now be defined by:

$$\Pr(\ln w_{iCt} < m_{Ct} | (\gamma_C - \gamma_R) \ln \eta^*_i + \mathbf{x}_i \cdot (\beta_C - \beta_R) > (\ln p_{Rt} - \ln p_{Ct})) = 0.5. \tag{23}$$

As in our earlier discussions, as the relative prices change, and assuming that $\beta_C \neq \beta_R$, the combination of values of η^*_i and $\mathbf{x}_i$ that satisfy the conditioning statement in (23) will vary. That is, the composition of workers in the sector in terms of both observable and unobservable characteristics will change, and sectoral wage changes will reflect both that change and changes in the sectoral task price. In this situation, holding the composition constant in terms of observable characteristics will go part way toward allowing us to identify movements in task prices alone.

How exactly to approach identification of task price trends in the presence of covariates depends on two factors: whether the β's are time varying, and whether elements of $\mathbf{x}$ are endogenous. We start by assuming that the $\mathbf{x}$'s are exogenous and return to address that issue in the next section. In that context, with time invariant β's, a simple way to identify movements in the p_{kt}'s is to generate estimates for workers with one specific value of the $\mathbf{x}$ vector since all types of workers face the same price trend. Holding the value of the $\mathbf{x}$ vector constant in this way, the expression in (23) is the same as what we worked with in earlier sections apart from the inclusion of the fixed component $\mathbf{x} \cdot (\beta_C - \beta_R)$. Thus, all of the same analysis goes through.[13] Alternatively, if the shape of the η distribution does not vary with $\mathbf{x}$ then one could run a median regression on the x vector, obtain residuals and work with those residuals as the equivalent of the wages in the expressions in the earlier sections. However, if the shape distribution of η (as opposed to just its location) does vary with $\mathbf{x}$ then this approach would not work since one would want to trim more from some covariate groups than others. The approach we describe below allows for the possibility that the shape of the η distribution varies with $\mathbf{x}$.

If, alternatively, the β's are time varying, we will see different median wage trends for different worker types defined by covariate values. Since movements in the task price for a sector will correspond to changes in productivity affecting all types of workers, we can capture task price

[13] Note that, even with time invariant β's the model could fit well known patterns such as increases in the BA/HS wage differential in recent decades. A change in the BA/HS differential arises in the model to the extent that BA and HS educated workers are differentially distributed across sectors. Then the wage differential will change if the sectoral compositions of the two groups change differently and/or the sector prices change. Whether these mechanisms are sufficient to explain observed movements in the BA/HS wage differential is potentially testable.

movements by obtaining the common component of (composition constant) wage movements for workers of all types. We do this by taking a weighted average of the (composition constant) wage changes for all types of workers with the weights being the proportion of workers who are of each covariate type in the base period.

The procedure we use to calculate this weighted average is to trim within groups defined by each possible value of the **x** vector according to the procedures developed earlier, re-combining the resulting, trimmed samples into an overall sample (using time constant weights) and, finally, obtaining the median of that adjusted sample. This, in principle, generates a trimmed sample with the η composition within each covariate group being constant. Since these sub-samples are re-combined with fixed weights, the end result is an overall sample with a time invariant η distribution and the covariate composition held constant at the base year value.[14]

The specific steps in our procedure are as follows (all carried out separately for different task groups):

1. Divide data into cells based on observable skill groups. We will define skill groups by age and education, and work with males and females separately.

2. Re-weight data in each cell to keep the number of observations constant at the base year (1990) value.[15]

3. For the Cognitive occupation group, compare the number of observations in the cell in a given year to the number in the base year.[16] If the current year has N more observations than the base year then trim N observations from the bottom of the current year. If the base year is larger, trim N observations from the bottom of the base year.

4. For each of the base year and current year, separately, pool the cell samples, weighting to maintain the true base year composition for each. Note that any base year trimming could be different for each current year since N will be different in comparisons of each current year to the base year. This means that there is potentially a different base year trimmed sample matched to each current year sample.

5. Calculate the median wage for the base year sample (m_t^B) and current year sample (m_t^C), and take the difference.

[14] Note that our final sample could contain a set of relatively high ability workers within one covariate cell and a low ability set in a different cell, depending on how the trimming proceeds. This is not a problem because we are working in differences.

[15] Note that if we pool the data across cells and obtain the median wages at this stage, the result will be a composition constant (in terms of observables) median wage series.

[16] For the middle skill occupations, such as R, deciding how many to trim and from where is more complex, as described earlier.

The result is composition constant and a bound on the selection-free median. Under our second set of assumptions, it is also a bound on the change in the task price. Under the stochastic dominance assumption, the other bound would be the actual, observable composition constant median wage changes.

3.1.6. Addressing Selection into Education

We return, now, to the possibility that there is a non-zero correlation between η^* and at least one element of $\mathbf{x}$. Our main concern in this regard is with education. In particular, it seems reasonable to assume that individuals differentially select into education based on their unobserved abilities. For example, we could also model education choice in an hierarchical version of a Roy model. In that context, if the proportion of people with a BA increases over time then the ability distribution in the BA covariate cells will change, with lower ability people being added. This violates our assumption of a time invariant η distribution. To the extent it happens, then the median ability in a particular task group within a cell defined by education and age will change even after trimming samples to account for the number of people entering or leaving the task. Changes in median wages for the trimmed samples will then reflect the change in abilities as well as the change in the task price. For this not to be true – for the covariate approach described in the previous subsection to generate consistent bounds on movements in the composition constant median wage - new additions to the set of university educated workers would have to have the same η^* distribution as those already in the university educated group, i.e., there would have to be no education related selectivity.

Assuming there could be an education selectivity problem, we could approach it using a more complex version of the Roy Model with individuals jointly choosing education and occupation. However, the education patterns in our sample period allow a simpler approach. If we think of education selection in the context of a simple Roy model with common costs of education and returns that vary based on a single ability factor then years with the same high education proportion will be years with the same distributions of ability within education groups. In Figure 1, we plot the proportion of individuals aged 22 to 30 who have a college degree or higher education separately for males and females. For males, there is a period with a relatively constant proportion in the late 90s and early 2000s. To highlight this, we draw a band that which is centred, vertically, on the proportion in 2000 with upper and lower edges that are plus and minus 2.5% of the 2000 value. Thus, the band corresponds to proportions that differ by no more than 5%. All of the years between 1995 and 2006 fall within this relatively narrow band and both the late 1980s and late 2000s values fall just outside it.[17] For females, the proportion rises continuously but does have a somewhat

[17]An implication of this figure is that the observed overall increase in the proportion of the male workforce with a college degree since 1980 has occurred largely because of the replacement of earlier, low educated generations by the more educated Baby Boomers and those who followed rather than because of ongoing increases in the proportion of

slower growth period between 1996 and 2001.[18] Based on this, we will work with young workers and emphasize comparisons among years with similar college education proportions as reflecting ability distribution constant comparisons within education groups.[19]

Fig. 1.— Proportion of college or More

3.2. Alternative Ability Models

We now re-examine the conclusions we have reached so far in the context of other assumptions about the errors in the wage and selection equations. These other assumptions correspond to other models of sector specific abilities and moving costs. As we will see, other ability models imply different trimming algorithms and, as a result, potentially different price trends. We do not have

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successive cohorts who obtained degrees. Beaudry and Green (2003) use this observation to obtain an instrument for changes in the US education composition.

[18]In this case, the band is centred on the 2002 values and is plus or minus 2.5% of that value.

[19]It is always possible, of course, that there are heterogeneous costs and returns to education and that the distributions of the costs and returns shift in such a way that the proportion of people with a college degree is constant but the ability composition of college graduates shifts.

a way to test among the models with our data. Instead, our approach is to see if the various approaches yield similar bounds on trends in this case. If they do, we see this as a basis for drawing strong conclusions. If they do not, it is useful to know the extent to which any potential conclusions depend on the specific model being employed.

3.2.1. Pure Single Ability Model

An extreme version of the hierarchical ability model arises if there are no ϵ's in the wage equation: both wages and selection depend only on a single ability factor. In that case, we would know exactly where movers between sectors fit in the sectoral wage distributions. For example, if we observe an increase in the number of workers in the C sector, $\Delta N_{Ct} > 0$, then we know that the lowest ΔN_{Ct} workers in the period $t + 1$ C sector wage distribution are those movers. We could then trim those ΔN_{Ct} observations from the period $t + 1$ distribution, find the median and difference from it the median wage in sector C in period t. In the more general hierarchical model, where movers could end up anywhere in the period $t + 1$ distribution, this generated the upper bound on the change in the sector C price. Under this more restrictive model, no bound is needed: the number calculated from the trimming exercise is the estimate of the price change. Essentially, this is the most extreme version of the monotonicity assumption.

3.2.2. Independent Productivity Shocks Model

The other main category in Willis (1986)'s taxonomy of selection models can be represented in our case by a model in which the η's and u's don't exist and the ν's enter the sector decision equation. Thus, the log wage would be written as:

$$\ln w_{ikt} = \ln p_{kt} + \nu_{ik} + \epsilon_{ikt} \text{ for } k \in \{C, R, M\}. \tag{24}$$

Again, we will assume that both the ν's and the ϵ's are mean zero, white noise variates – independent of each other, across time, and across sectors for the same person. Importantly, in this model, there is no natural ordering of occupations. People can be good lawyers but bad carpenters, with the draws on how good a person is at each being independent.

The index determining the choice of the C versus the R sector, again assuming that ϵ_{ikt} does not enter the selection process, is given by:

$$z_{iCRt} = (\nu_{iC} - \nu_{iR}) - (\ln p_{Rt} - \ln p_{Ct}). \tag{25}$$

The logic of the Roy model implies that addressing selection with these ability assumptions is easier than with the Hierarchical Ability model. One can show that with the Independent Shocks model, the wage distribution of people who would be in a sector under both period t and period

$t+1$ prices will first order stochastically dominate that of people who would be induced to join the sector because of an increase in its price between period t and $t+1$. The logic underlying the latter result again comes from the monotonicity implicit in the selection model: the people induced to join a sector by a price increase will be of lower ability in that sector than those who were in at the lower price, otherwise they, too, would have already been in the sector. With sector specific abilities being independent, workers may be moving between any pair of sectors in a given period depending on the set of relative price changes (e.g., unlike in the Hierarchical Model, we could see workers moving from $C \rightarrow M$ and from $R \rightarrow C$ in the same period). But, again because of the independence, in considering changes in a specific sector, there is no relevant information about that sector's abilities in where new workers come from or departing workers exit to. That means that only the net change in the size of the sector matters for the ability composition in the sector.

Based on this, we can form two bounds: 1) trim the net change in number of workers from the bottom of the period $t+1$ wage distribution if the sector grew and from the bottom of the sector t distribution if it shrank; and 2) the actual changes in the median wages (under the Stochastic Dominance assumption). Notice that this is the same as the bounds for the C sector in the Hierarchical Model since all workers enter and leave that sector at the bottom of the distribution in that model. But it is different from the R and M sectors in the Hierarchical Model. For those sectors, workers entered and left from either the top of the distribution or from both the top and bottom, depending on the number of sectors. Finally, as with the Hierarchical Model, we will allow for the Home (nonemployment) sector. Movements in the employment rate will affect the amount of trimming done in the other three sectors and will alter results to the extent that changes in the employment rate are not simply shared across the other sectors in proportion to their size (i.e., to the extent that the proportion of all people employed in C, R or M moves differently from the proportion of workers employed in those sectors).

3.2.3. Combination Model

Now consider a case that is a combination of the Hierarchical and Independent Shocks model. In this case, the log wage would again be written as:

$$\ln w_{ikt} = \ln p_{kt} + \gamma_k \ln \eta_i + \nu_{ik} + \epsilon_{ikt} \text{ for } k \in \{C, R, M\}. \tag{26}$$

Both ν and η enter the selection process:

$$z_{iCRt} = (\gamma_C - \gamma_R) \cdot \eta_i + (\nu_{iC} - \nu_{iR}) - (\ln p_{Rt} - \ln p_{Ct}). \tag{27}$$

First, consider the C sector. Since this continues to be the top occupation in terms of selection based on the η's, entering or departing workers from the sector will tend to come from the bottom of the sector specific η distribution and will also come from the bottom of the ν_C distribution for the reasons discussed in the independent shocks model. Thus, the bounds for this sector are the same as in both the previous models.

For the R sector (and also the M sector in the four sector model), the situation is different. In particular, suppose that p_{Rt} increases relative to all other prices. Inspection of (27) indicates that those entering from the C sector will tend to be at the top of the η distribution for the R sector, while those entering mainly because of comparisons of ν values will tend to enter at the bottom. This means that it is not possible to tighten the bounds using stochastic dominance assumptions for the R and M sectors. As a result, the bounds for the C sector are the same as for the Hierarchical and Independent Shocks models but for the R and M sector we will use the extreme bounds formed by trimming the net change in the sector size from either the top or the bottom of the period $t+1$ distribution (if the sector is growing) or the top or bottom of the period t distribution (if the sector is shrinking).

Finally, one could introduce shocks to the costs of being in a sector that do not directly affect productivity (the u's in the initial model). If these are independent of all other shocks then the resulting model is the same as the Combination Model in terms of its implication for bounding. This is true because the implications of the u's for bounding are the same as for the ν's. That is, decreases in these costs for a particular sector will lead people to enter the sector and the entrants will tend to be at the lower end of the wage distribution since those with lower costs of being in the sector would tend to be already working there. If, however, the cost shocks and the productivity shocks for a sector are positively correlated then one can no longer make stochastic dominance arguments for anyone and the extreme bounds are the only ones that are clearly proven.

4. Data and Implementation

4.1. Data

The data we use for our empirical work comes from the the Current Population Survey's Outgoing Rotation Group, from the years 1984 to 2013. Our initial extraction includes all individuals aged 18-64 years with positive potential experience, and excludes full- or part-time students. Following Lemieux (2006), we use the hourly wage as our wage measure and do not use observations with allocated wages when calculating wage statistics.[20] Wages and employment status refer to the week prior to the survey week, and we only use wage and occupation data on individuals who are currently employed in the reference week. Our main empirical work focuses on a subset of these data, with the goal of capturing workers at the beginning of their careers. To do this, we select young workers, between the ages of 18-30, with no more than 5 years of potential experience. We discuss the rationale for this decision in detail in the following subsection.

Following Acemoglu and Autor (2011) and the extensive literature on polarization they survey, we aggregate occupations into three broad groups: Cognitive (occupations with a high intensity of

[20]The data are processed as in Beaudry, Green, and Sand (2013) who provide detailed information on data processing. We begin our series in 1984 because this is the first year in which we can identify students.

abstract thinking tasks that are often viewed as complementary to capital and organizational forms embedding information technology (IT)); Routine Production and Clerical (blue-collar and white-collar occupations intensive in routine tasks that can be easily substituted for by IT); and Manual (service and manual occupations that tend to be low skilled but not easily substituted for with IT). The occupation codes are based on 1980/90 Census categories and are consistent from 1983-2002. For post-2002 data, we use Bureau of Labor Statistics cross-walks to convert the data into 1980/90 categories before aggregating into the three broad occupation categories we use below.[21]

4.2. Which Wage?

There are a variety of choices for the wage measure to use in trying to uncover task price movements and, as we will see, which one we use has important implications for our conclusions. Our decision in this regard is influenced by the literature suggesting that implicit contract considerations are important for understanding wage movements (e.g. Beaudry and DiNardo (1995); Ham and Reilly (2002)) and papers that suggest that individual wages are sticky during a job or even during a career (Oreopoulos 2012; Barattieri, Basu, and Gottschalk 2014). In the spirit of those literatures, in Figure 2, we plot smoothed profiles of median wages for cohorts of men with a high school or less education where we define a cohort as the set of men who turned 25 in a given pair of years. Thus, the line starting farthest to the left corresponds to the group of men who turned 25 in 1984 or 1985. We use a synthetic cohort approach, obtaining the median wage for the 1984-85 cohort in 1986 as the median wage for 26 and 27 year olds in 1986 in our CPS data, for example. The smoothing consists of a linear spline with a knot point at 10 years after the cohort start date. The key point from this graph is the persistence in the experience of the different cohorts. Successive cohorts entering between the early 1980s and early 1990s, and again across the 2000s have lower and lower starting wages, and maintain their relative rankings in the future. When a cohort enters both in terms of the business cycle and the long term trend matters for the wages it will earn even 20 years later.

It is useful to consider the options we face for wage measures in the light of this persistence. The most obvious measure is the median wage across all workers in a given occupation group in a year. That measure faces two problems. The first is the problem of non-random selection which motivates our bounding approach. The second is that we want, as much as possible, to track the task price in each year as a reflection of the demand and supply shifts in that year. But Figure 2 makes evident that the wages of older cohorts in a given year reflect not only current economic forces but also productivity and supply shifts in the past, particularly those from when they entered the labour market. Thus, the median wage for all workers will move as a weighted average of past task price changes, making the identification of the timing of changes in task price trends difficult.

[21] Details on adjustments and cross-walks used in generating consistent occupation categories are given in Beaudry et al. (2013).

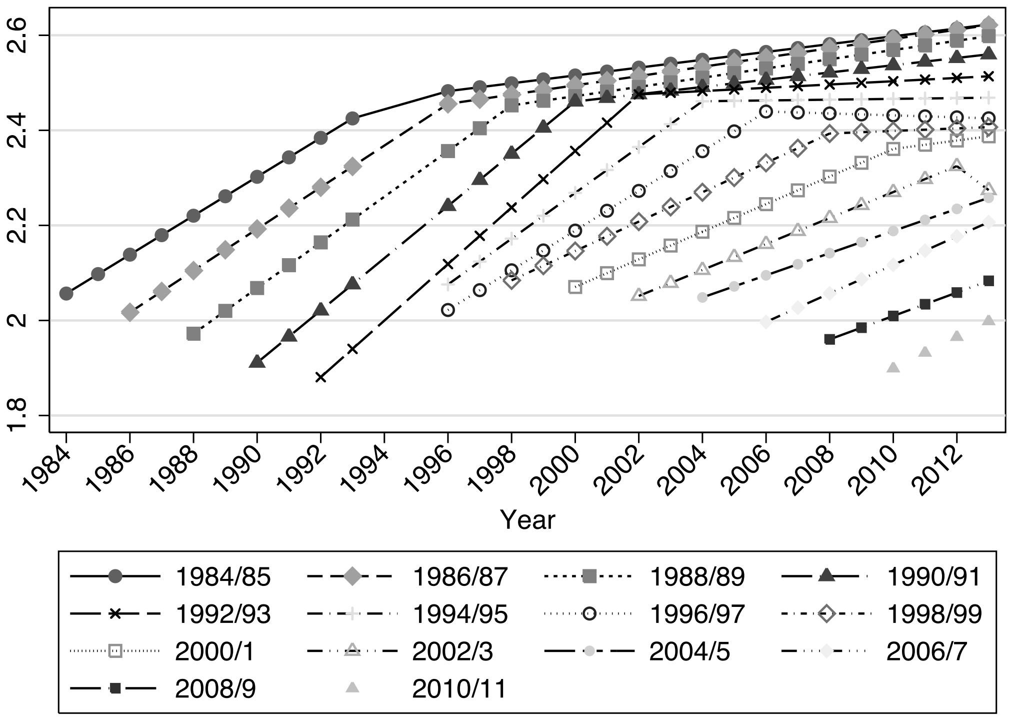

Fig. 2.— Smoothed cohort wage profiles for High School or Less educated Men

Another possibility is to track the median wage for a given cohort over time. In particular, with panel data, one can investigate the year to year changes in wages for a specific set of workers. In the Roy Models described earlier, workers choose their sector based on time invariant abilities. In that context, following a set of workers, regardless of whether they are highly selected, necessarily holds constant ability and implies that their wage movements must reflect movements in task prices rather than changes in selection (at least once one controls for the idiosyncratic component of wages through averaging across workers). This is the approach pursued in Cortes (2012). But the type of stickiness of wages inherent in implicit contract models and evident in Figure 2 implies that the wage movements for a group of workers reflect factors other than current changes in task prices. For example, Figure 2 indicates that following the wages of a group of older workers would lead to the conclusion that task prices change vary little over time. In addition, the steep slopes of the profiles at younger ages reflect elements such as human capital investment that will be hard to separate from task price movements when following a set of younger workers. We conclude from this that addressing selection issues through following workers in panel data is unlikely to provide a clear picture of movements in task prices.

Our approach, instead, is to use the wages of young workers - essentially the wages at the start of the cohort profiles. In particular, we work with the wages of workers who are under age

30 and have 5 or fewer years of predicted experience (age - years of schooling - 5). As we show in the appendix, in an implicit contract model with trends, these wages will reflect the expected value of marginal product of newly hired workers. To the extent that future productivity is difficult to predict (such as, for example, if task prices follow a stochastic trend) the wages will largely reflect worker value of marginal product at the time of entry to the labour market. In the context of the wage determination model we consider, that value will move across cohorts because of a combination of changes in the task prices and changes in the ability composition of the workers selecting into each sector. We address the latter through our bounding approach.

Apart from the argument that they will better track current movements in task prices, there are several other reasons to focus on wages for young people. As we document in the Data Appendix, both union membership and coverage increase sharply with age, while employment in the private sector declines sharply with age. During the 1990s, in our data, less than 10 percent of employed men and women under the age of 30 worked in the government sector. To the extent that wages of union workers and those working for the government are determined by non-competitive factors, these facts suggest that working with younger workers is better suited to our goal of identifying task prices being set through competitive forces in the labour market. In addition, data issues imply that wages of younger workers are better measured in our data. For instance, top-coded wages are much more likely to occur among older workers. While top-coding in general is rare in our data, allocated wages are a much bigger concern, and in studies of wage trends, these workers are often excluded from the analysis (Lemieux 2010). What is less well-known about allocated wages is that their incidence is much higher among older workers. For example, in our data, about a 1/3 of men over the age 45 have their wage allocated, compared to about 1/5 for those under 30. Further, the wage measure we use is the log of hourly wage. In our data, the hourly wage is directly measured, rather than calculated from annual earnings, for workers who are paid by the hour. The vast majority of young workers report being paid by the hour, and this fraction falls after about the age of 30. Finally, working with cross-cohort variation for young people allows us to take advantage of the relative stability of the proportion of each cohort obtaining a university degree described in section 3.1.6.

Attempting to identify task price movements with cross-cohort variation for young people does require important assumptions. As we have already discussed, a key one in this regard is that the distributions of ability and idiosyncratic components such as measurement error must be stationary over time. This assumption is not needed in the panel data approach to the selection problem apart from assuming that individuals do not update their abilities over time. In addition, if we introduce human capital considerations, we need to assume that workers do not dedicate differing amounts of their time to human capital acquisition in different cohorts. If they did then part of any cross-cohort wage movements would reflect these investment differences. Heckman, Lochner, and Taber (1998) and, following them, Bowlus and Robinson (2012) focus on this human capital issue and argue for identifying human capital price movements by working across cohorts but focussing on individuals near age 50. The key idea is that at that point in the lifecycle human capital investment has stopped and depreciation hasn't started so that changes across cohorts will not reflect human capital effects. We re-estimated our specification using that age group rather than workers under age 30. The result is very different implied task price patterns, including rapidly falling cognitive task prices before 2000 – in a period when most observers believe new technologies are complementing cognitive abilities. Given our earlier arguments that wages in the over age 50 group likely strongly reflect prices and productivity from much earlier years, we believe it is preferable to focus on younger workers and we pursue that course here.

5. Results

5.1. Observed Wage Trends

In Figure 3, we plot median hourly log wages for workers of all ages for the three occupation groups, separately for men and women. For ease of comparison, we plot the difference between the log median wage in each year and the log median wage in 1984. When calculating the median wage, we delete observations with allocated wages but we do not trim the remaining sample for outliers.

The sectoral wage movements for men fit with the argument in papers such as (Autor et al. 2003, 2007; Acemoglu and Autor 2011) that over the last three decades, the U.S. has undergone a polarization in wages, with wages for both low skilled M sector workers and high skilled C sector workers growing relative to wages in the R sector. For both genders, much of the polarization occurred in the late 1990s. After 2000, the sharply increasing wage trends of the 1990s give way to flat or even declining trends. Importantly, though, one would conclude that cognitive wages have continued to increase, which could imply that biased demand in favour of those tasks has continued as well.

As discussed previously, shifts in the wage series can arise because of changes in task prices or because of composition shifts within each occupation. Composition shifts might occur because of shifts in the age structure due to the ageing of the baby boom cohort or because of increases in education during the sample period. To account for changes in composition, we perform a simple reweighting exercise. In particular, we follow Lemieux (2010) and divide the data into demographic cells based on five education groups and eight age groups. For each occupation, we create a set of fixed weights based on the average proportion of each of the demographic groups during the entire sample period. Using these weights, we recalculate occupational median wage series holding the demographic mix of each occupation constant at the average fraction of all years combined. In Figure 4, we report the results of this exercise separately by gender.

This figure is our first indication that composition does matter in this period. For men, real wage declines for the R sector double once we control for age and education composition. Perhaps most strikingly, for the M sector, a pattern of modest overall gains, with wage increases in the 1990s and a flat wage trend after 2000, is converted to one of general decline, with wages falling

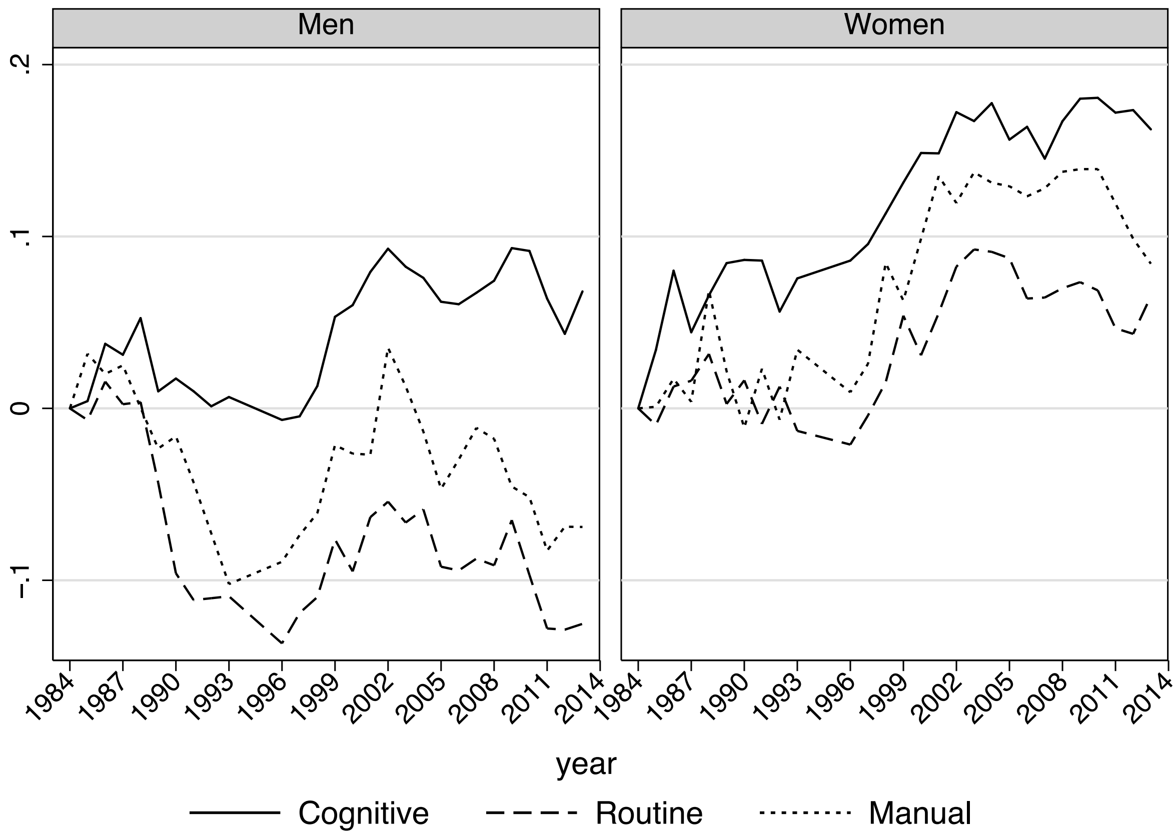

Fig. 3.— Indexed Median Wage by Occupation Group: All Workers

particularly strongly after 2000. For both men and women, once we take account of education increases and the rise in the average age of the workforce, wages in all sectors fall after 2000.

As discussed in the previous section, our main focus will be on younger workers at the beginning of their careers. In Figure 5 we plot indexed wages by occupation group for our sample of young workers, where, again, we have held the education composition of each occupation constant at the average for the entire sample. For this age group, the wage movements are actually less dramatic than for the overall age sample but continue to show the pattern of increases in the 1990s followed by declines after 2000. For males, there is no evidence of polarization before 1999 since all three task prices move together up to that point, and only slight evidence of a polarizing pattern after that. For females, the main sectoral difference is the strong rise in wages in the M sector relative to the other two in the late 1990s.

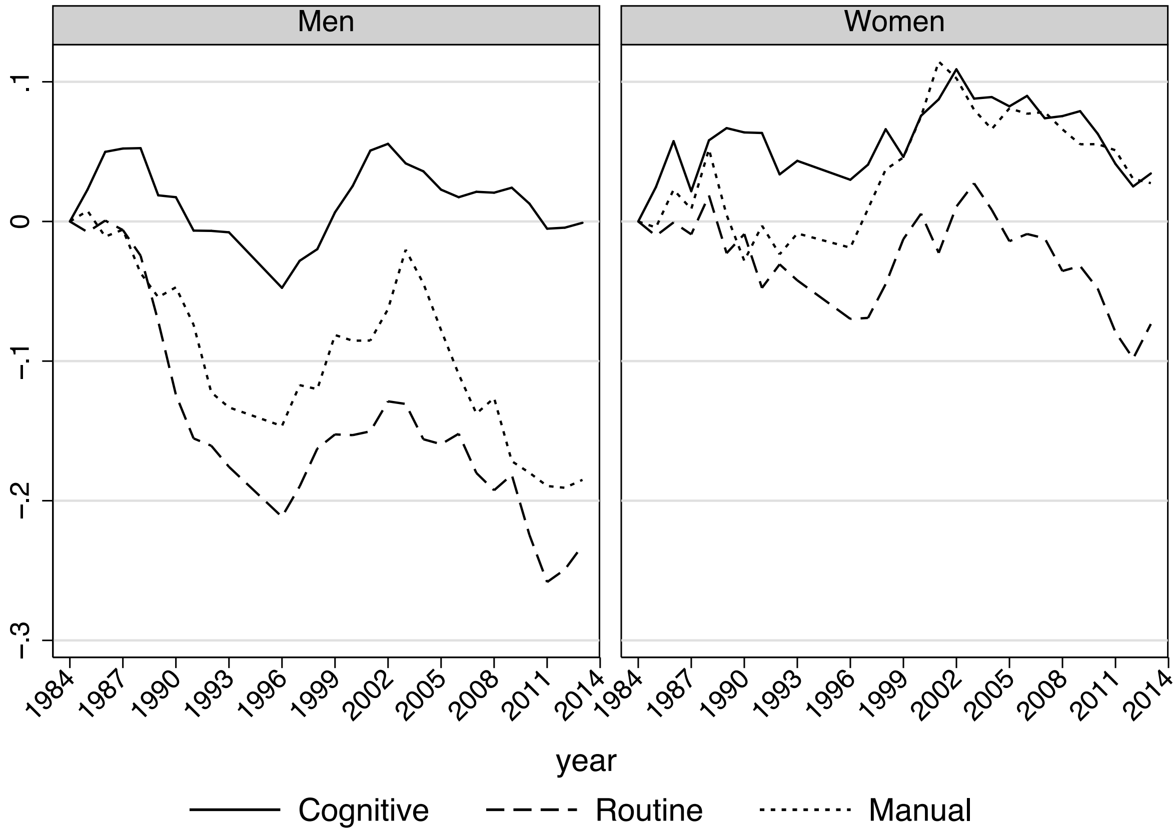

Fig. 4.— Indexed Median Wage by Occupation Group: All Workers, Composition Adjusted

5.2. Bounds

We turn, now, to our main empirical results: those showing our constructed bounds for movements in the median sectoral wages when both the composition of observables and unobservables are held constant. All results are for the young age/experience sample. The bounds depend on movements in the median wages associated with each task sector but also on the movements in employment within each. It is the changes in employment that determine the maximum potential extent of selection related effects. In Figure 6, we plot the proportion of our young sample in each of our four sectors relative to the 1984 base year. We normalize to 1984 because this helps see within-sector movements, which are what are used in the trimming exercises. For both men and women, the proportion in Cognitive task occupations grows by between 15 and 20% between 1984 and 2000, offset primarily by declines in the proportion in Routine occupations. This fits with standard discussions about the relative demand effects of the IT revolution. After 2000, the proportion in Routine occupations continues to decline but the Cognitive occupation proportion also falls for both men and women. This is offset by a substantial increase in the proportion non-employed

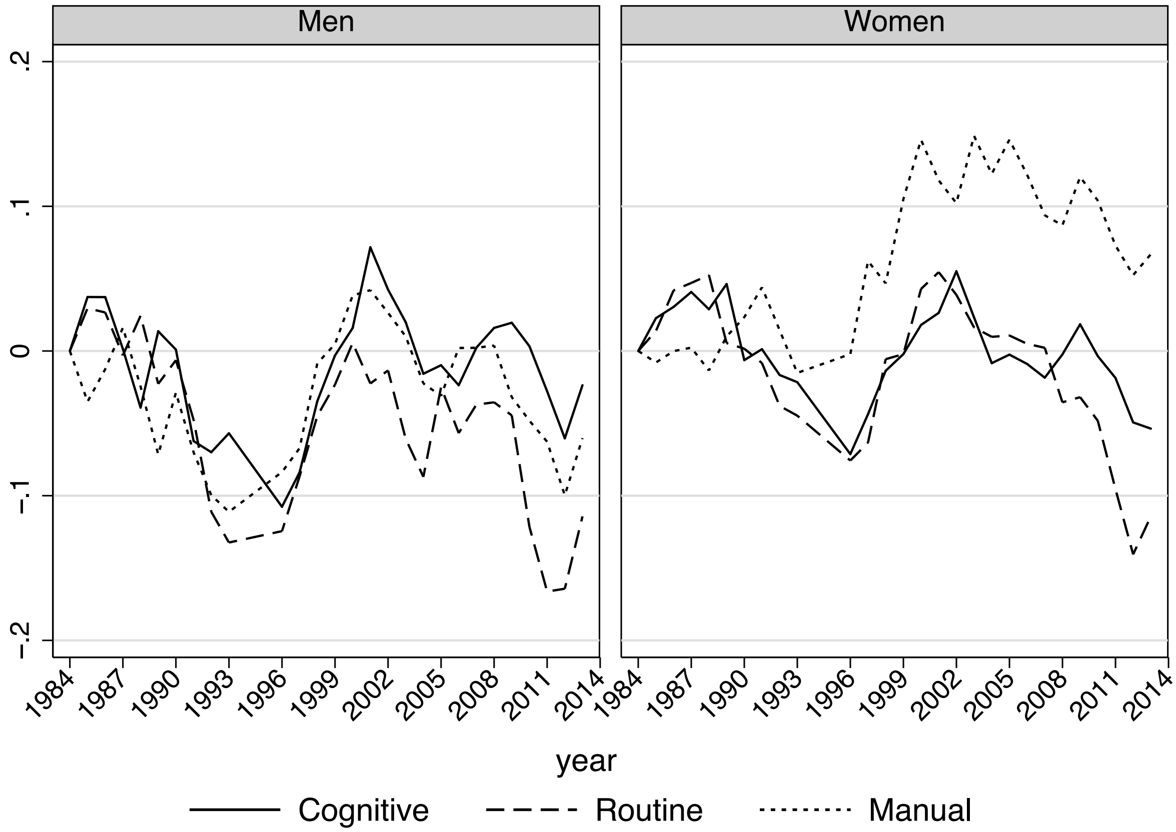

Fig. 5.— Indexed Median Wage by Occupation Group: Young Workers, Composition Adjusted

relative to the base year for young men and by increases in both the proportion non-employed and the proportion in manual occupations for young women.

Beaudry, Green, and Sand (2014) provide an explanation for the change in patterns after 2000 that is based on the maturing of the IT General Purpose Technology. Regardless of the driving force, it is evident that the movements in proportions within sectors are sufficiently substantial to raise concerns about changes in the ability levels of the workers selected into each sector over time. In addition, the size of the non-employment movements, especially after 2000, lend support to our decision to treat non-employment as sector in order to incorporate the potential effects of those movements on the task prices in the other sectors.

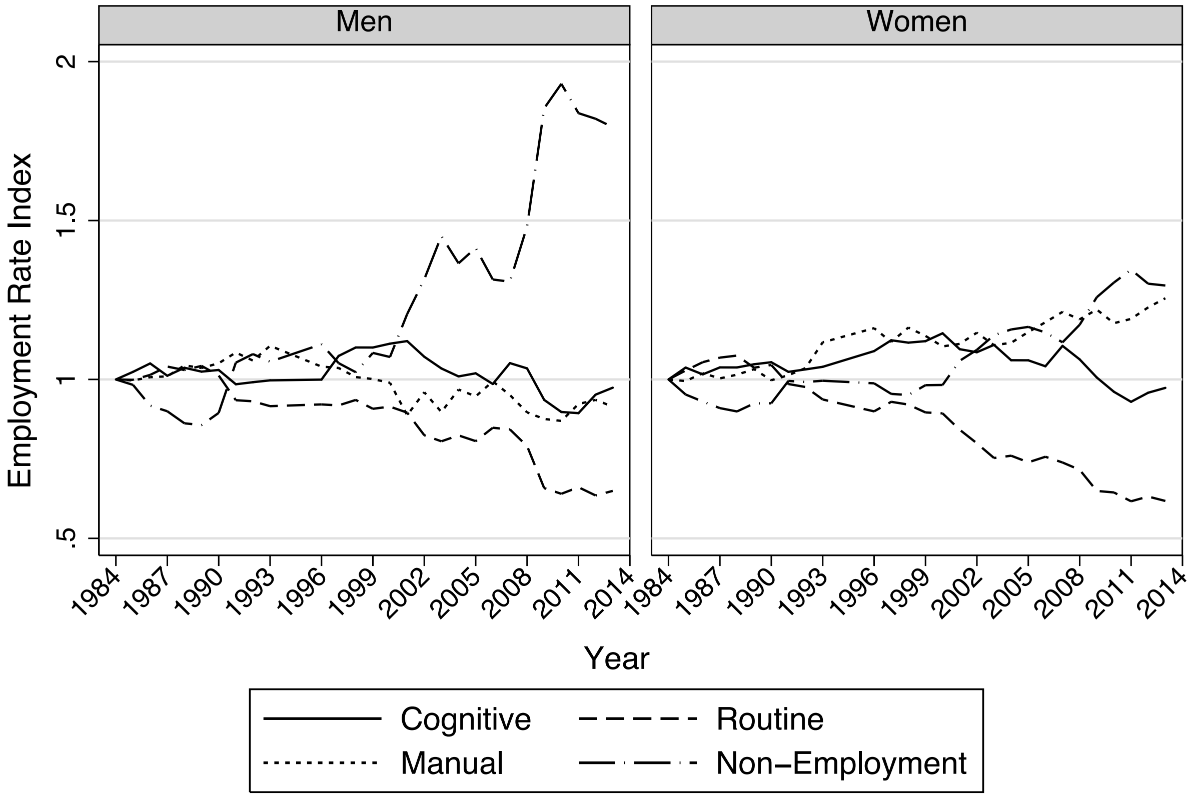

Fig. 6.— Proportions in Each Task Relative to 1984, Young, All Education

5.2.1. Cognitive Task Sector

In Figure 7, we present plots of the two bounds for the cognitive sector task price along with a bootstrapped confidence interval for the line where we trim from the bottom of the wage distribution.[22] It is worth recalling that the same procedure is used for forming bounds for the Cognitive task price under all three of our models. The two bounding lines in the figure correspond to changes relative to the base period, 1984, since it is changes that our procedure allows us to identify. As the sector grows and contracts, it is possible for the lines to cross since trimming is done either in the current year or the base year depending on growth versus contraction. Thus, unlike standard bounding, in any given year, one line shows the upper and the other the lower bound on the change relative to the base year but which is upper and which is lower can vary. To avoid

[22]To form the confidence interval, we draw 100 samples of the data with replacement. We obtain the standard deviation of the value of the bound in each year across the 100 samples. The plotted confidence interval is plus or minus 1.96 times that standard deviation.

confusion, we will refer to the bound that is equal to the covariate constant median wage as the Stochastic Dominance (SD) bound since it is implied by arguments about stochastic dominance. We will call the other bound – the one formed by trimming from the bottom of the distribution – Trimmed (T) bound. We do not plot the confidence interval for the line corresponding to the SD line order to keep the figure readable but have tested for differences between the two lines. Roughly speaking, in the ensuing figures whenever the SD line lies outside the confidence interval for the T line, the two lines are statistically significantly different at the 5% level.

The dashed line in figure 7 corresponds to the SD bound. For males, in the left panel, it increases by approximately 1% between 1990 and 2000 but by over 15% between its low point in 1996 and its peak 5 years later. In contrast, between that peak and the end of our sample in 2013, it falls by 9%, with about half of that happening by the start of the recession in 2008. The bound formed by trimming from the bottom of the distribution shows a greater run-up in the 90s (experiencing a 6% increase between 1990 and 2000, and a 20% increase between 1996 and 2001) but also a larger decrease, ending up at the same level as the covariate constant median in both 2008 and 2013. It is also the case that the lower end of the confidence interval in 2001 is above the upper end of the confidence interval in 2012, indicating that we would not be able to reject that cognitive task prices fell over this decade. For females, the pattern is similar but more muted. Since, as we showed earlier, the SD bound is the same as the changes in the covariate constant median, these results can be re-stated as showing that once we take account of selection on unobservables, the increase in the cognitive task price in the 1990s and its decline in the 2000s are at least as large as what are obtained from the simple exercise of plotting wage changes while holding the observable covariate composition constant.

The `X`'s plotted on the T line correspond to years with similar education composition. We define education constant years by first finding the proportion of individuals for a given gender in each of four education categories (high school drop-out, high school graduate, some post-secondary, and college degree or higher) in each year. We then calculate the Euclidian distance between the vectors of those proportions and the value of the vector in 1999 (a year chosen as the approximate mid-point of what figure 1 suggests is the largest set of education constant years for males). We define "constant" education years as ones where the absolute value of the difference is in the bottom 10% of all the values (roughly less than a value of .02). This yields the years 1996 through 2005 as education constant years for men, implying that the main pattern of a strong run up in the task price in the late 1990s followed by an almost equally strong decline after 2000 is not driven by education related selection on unobservables. It is worth noting that while we plot the `X`'s on the T line for simplicity, the same arguments apply to the SD line. For women, we repeat the same exercise as for men but use 2002 as the base year (the middle of the flattest education composition period for women). As seen in Figure 1, the potential constant education range is much narrower but still falls over a set of years that reveals the increase in the cognitive task price in the late 1990s and the turning point near 2000.

In the appendix, we present the same plot as figure 7 but restrict the sample to those with a college or higher education. The patterns for both males and females are similar to the all-education plot but show somewhat larger movements. The similarity of the figures at the different levels of education aggregation is reassuring in that it suggests a common trend for the task price whether we control for covariates through an averaging approach or by examining one covariate group.

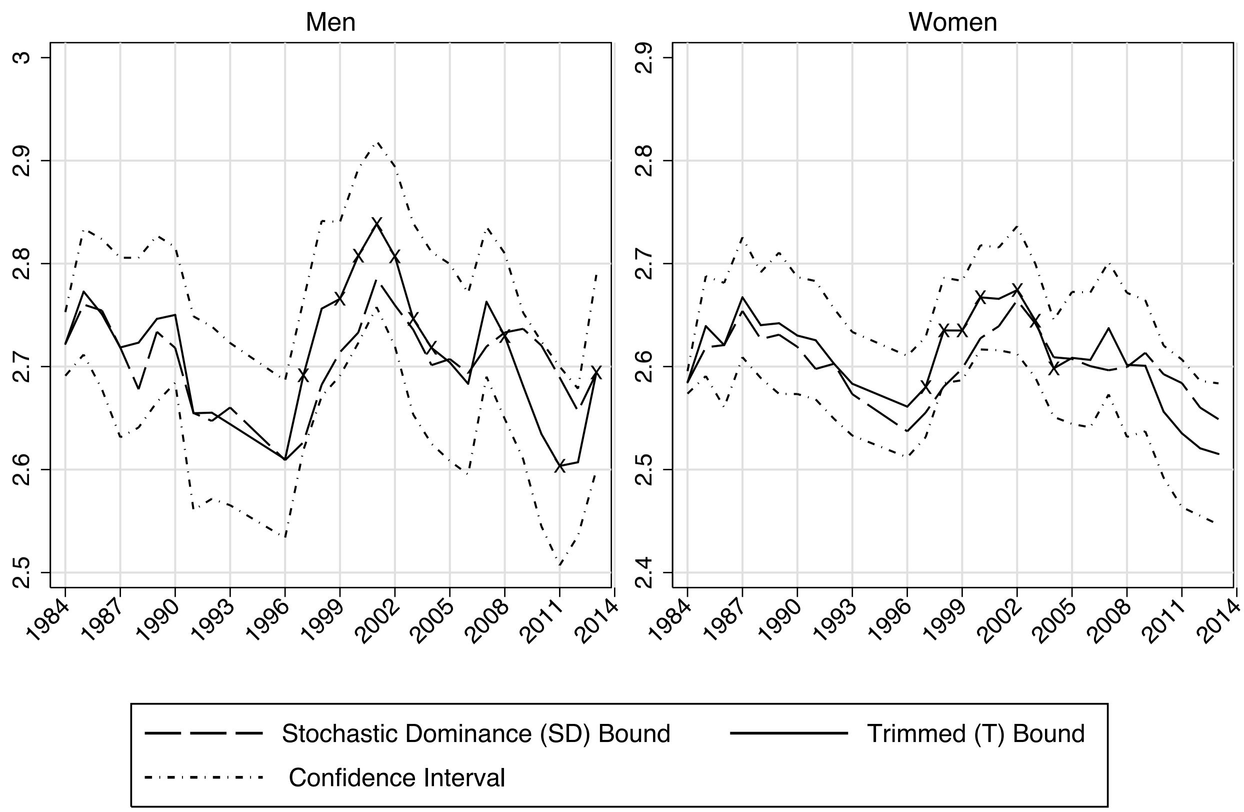

Fig. 7.— Cognitive Task Price Changes, Young, All Education

Recall that our conclusions about task price movements from figures like 7 can be altered if the factor loading on ability is changing at the same time. To gauge this, in Figure 8, we plot the difference between the 75th and 25th percentiles of the trimmed samples. The general trend for the difference is quite flat for males up until the early 2000's after which it appears to increase to some extent. However, given that the lower edge of the confidence interval never exceeds the upper edge from earlier years, we cannot reject the hypothesis that the difference does not change over time. This would imply that the median wage changes in the earlier figures correspond to changes in the task price. However, based on our earlier discussion, even if the the inter-quartile range is rising after 2000, this would not over-turn our earlier conclusions. In particular, we argued that if the inter-quartile range is rising then observed wage trends are under-statements of the extent of the fall in the task price. Since the bounds on the composition constant median wage changes imply a decline in those wages, the task price change would be, if anything, more negative than what the wage bounds alone imply.

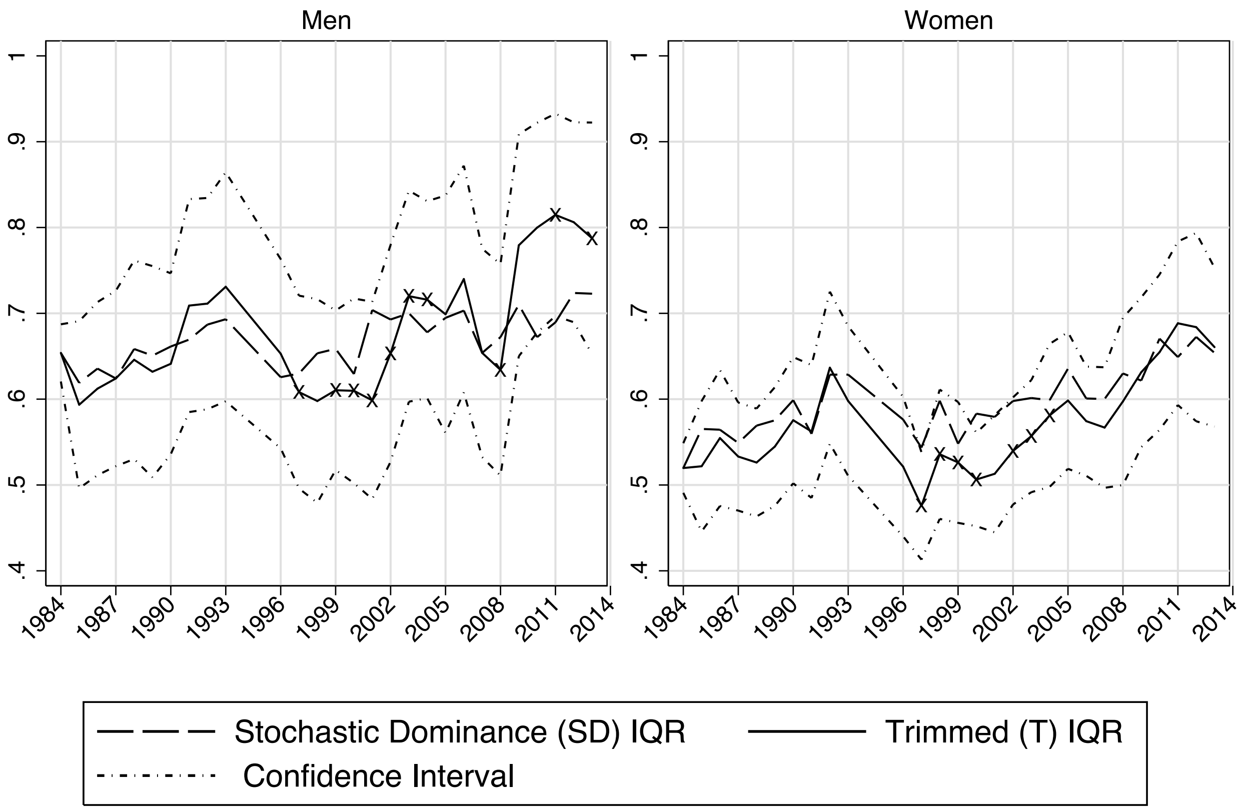

Fig. 8.— Interquartile Range for Cognitive Task Price Changes, Young, All Education

5.2.2. Routine Task Sector

In Figure 9, we present plots of the bounds formed for the Routine Sector task price under the Hierarchical Model. For the Routine Sector, the specific model of ability we assume alters the way the trimming is done and results in different bounds. In this figure, with Hierarchical Model trimming, the strong impression is of a long term ratcheting down of wages, with significant drops during recessions that are only partially offset by increases in subsequent booms; a pattern that continues to be evident if we focus on the education constant (X) years. For both men and women, the SD bound indicates a decline in the task price over the whole period on the order of 12%. For the bounds formed by trimming the bottom tail of the distribution, the decline is on the order of

20% between 1984 and 2007 but this is followed by a much larger drop during the 2008 recession. The post-2000 declines in the T bound are statistically significantly different from those in the SD bound. The sharp post-2008 drop in the T bound is an artifact of the Hierarchical Model trimming protocol. The large increase in the share of workers in the H sector (i.e., non-employed sector) is necessarily seen as being generated as a flow out of the bottom of the M sector in the Hierarchical Model. Since, in reality, not all of the increased number of non-employed workers would have otherwise been in the M sector, the net change in the M sector will be much smaller than the increase in the H sector as the U.S. entered the recession. In the Hierarchical Model this implies that there must have been an offsetting entry of workers to the M from the R sector. This then requires us to trim a considerable number of workers from the bottom of the base period R wage distribution, which yields large drops in the trimmed sample median wage.

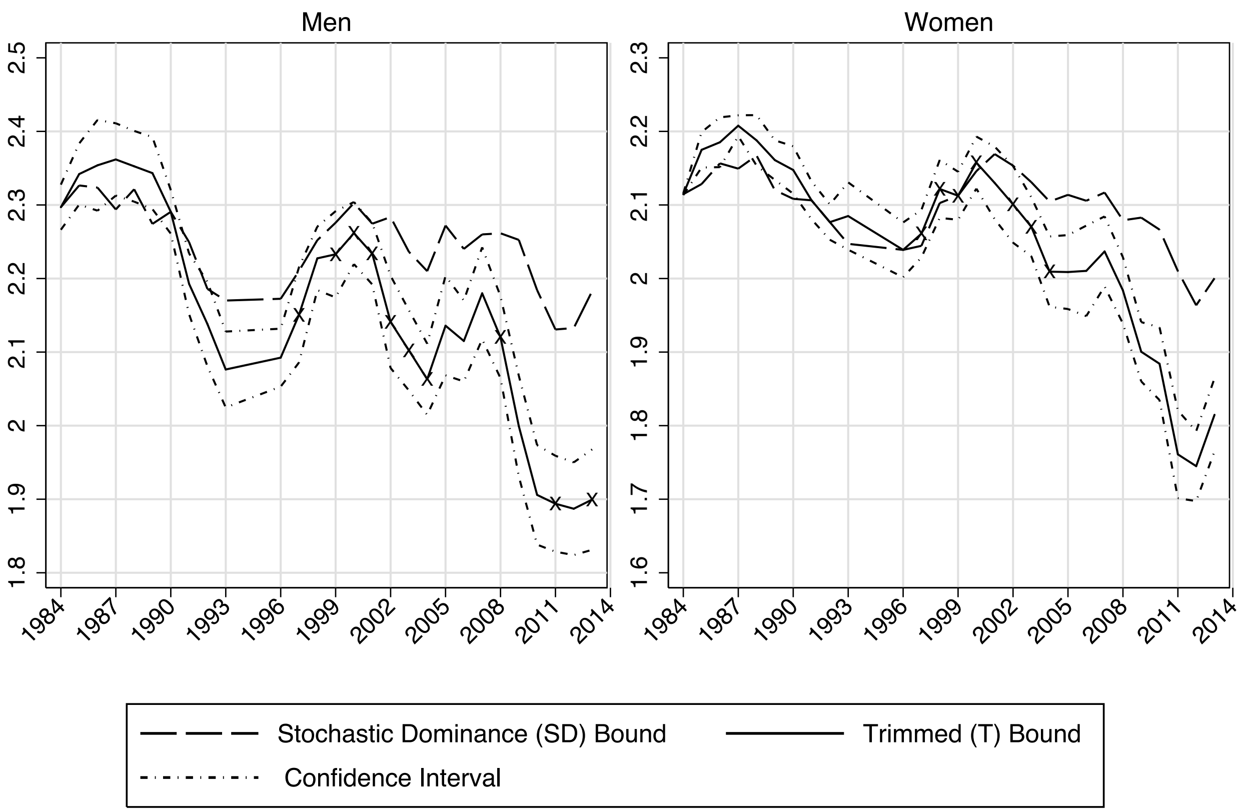

Fig. 9.— Routine Task Price Changes, Young, All Education, HM Trimming

In Figure 10, we plot the bounds on the interquartile differences for Routine sector wages. For the untrimmed samples associated with the SD bound, the range shows a decline in the mid-90s but it otherwise follows a flat trend. Thus, the 25th, 50th and 75th percentiles of the wage distribution move down together. However, once we trim according to the extreme version of the Hierarchical Model, the trend for the inter-quartile difference is flat until about 2000 for both men and women but then rises strongly (and statistically significantly). This rise is driven by a stronger decline in the 25th than the 75th percentile of the trimmed samples after 2000. The implication is that there is something of a polarization within the Routine sector after 2000: the 25th percentile of the trimmed sample (which would be more like the 40th percentile of the untrimmed sample) declines more than the 25th percentile of the untrimmed sample. In terms of implications for bounds on task prices, the rise in the inter-quartile range after 2000 implies an increase in the ability factor loading after that year and that the decline in the task price is even larger than the large declines we observe in the bounds on the composition constant median wage.

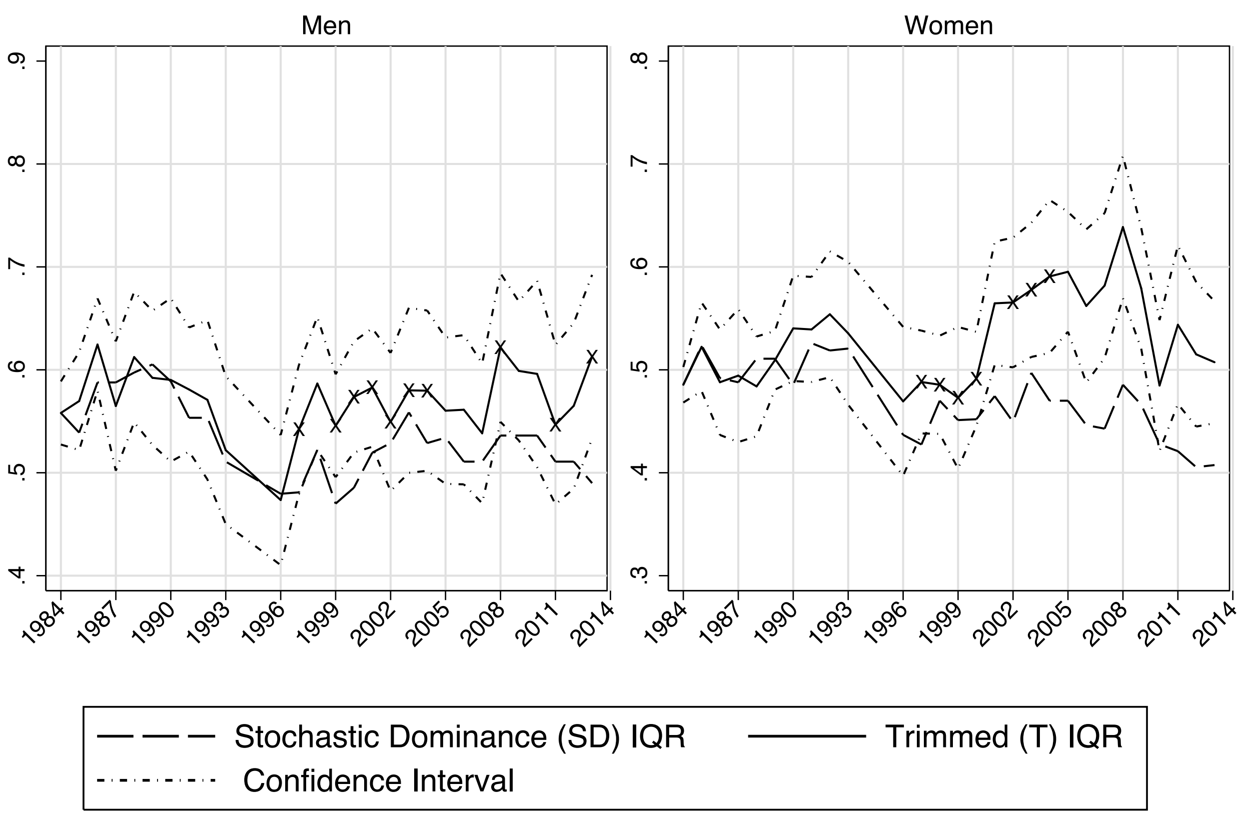

Fig. 10.— Interquartile Range for Routine Task Price Changes, Young, All Education, HM Trimming

Figure 11 contains the bounds for the case where we trim according to the Independent Shocks model. Recall that this means we either trim observations equal to the net change in the number of workers in the sector from the bottom of the wage distribution, or (using Stochastic Dominance) we don't trim at all. Despite the differences in trimming, the patterns are very similar under the two models, with the T bound in each case declining nearly continuously since the 1980s, apart from the late 1990s, for both males and females. In contrast, in the Combination Model Figure 12, the bounds move very similarly up to 2000 but part company in recent years.[23] In particular, the bound formed by trimming from the bottom of the distribution falls sharply after 2000. This is, in fact, the T bound from the IS model. In contrast, the bound formed by trimming from the top of the distribution rises between 2000 and 2008, particularly for men, before falling to a level that is comparable to the 2000 value in 2013.

Fig. 11.— Routine Task Price Changes, Young, All Education, IS Trimming

It is instructive to think about why the Top Trimmed line in the Combination model figure is different from the Hierarchical Model T pattern. As we saw in figure 6, before 2000, the size of the Routine sector declined but the size of the Cognitive sector increased. In the Hierarchical Model this

[23]We do not plot confidence intervals in order to keep the figure readable. For the years after 2000, the two bounds are statistically significantly different from each other.

would be treated as workers leaving from the top of the Routine sector to move into the Cognitive sector. Thus, in that period, the Top Trimmed bound and the Hierarchical Model Trimmed bound would be approximately the same. After 2000, the Routine sector declines even more strongly but, at least for males, the decline in the Cognitive sector is almost as large. In the Hierarchical model, this would be treated as adding the number of workers who left the Cognitive sector to the Routine sector while moving enough workers to make up the Routine sector decline from the bottom of the distribution into the Manual sector. The net result will be similar to just trimming from the bottom of the Routine sector distribution. In contrast, because the Routine sector is declining in size, the Top Trimmed bound will involve trimming more and more workers from the top of the base period Routine distribution, implying a lower and lower base period median and a larger increase. This demonstrates the importance of assumptions about the form of the selection model. With an HM or IS model, the bounds clearly indicate a decline in Routine task prices after 2000 while for the Combination model, one bound shows a decline while the other shows an essentially zero change between 2000 and 2013.

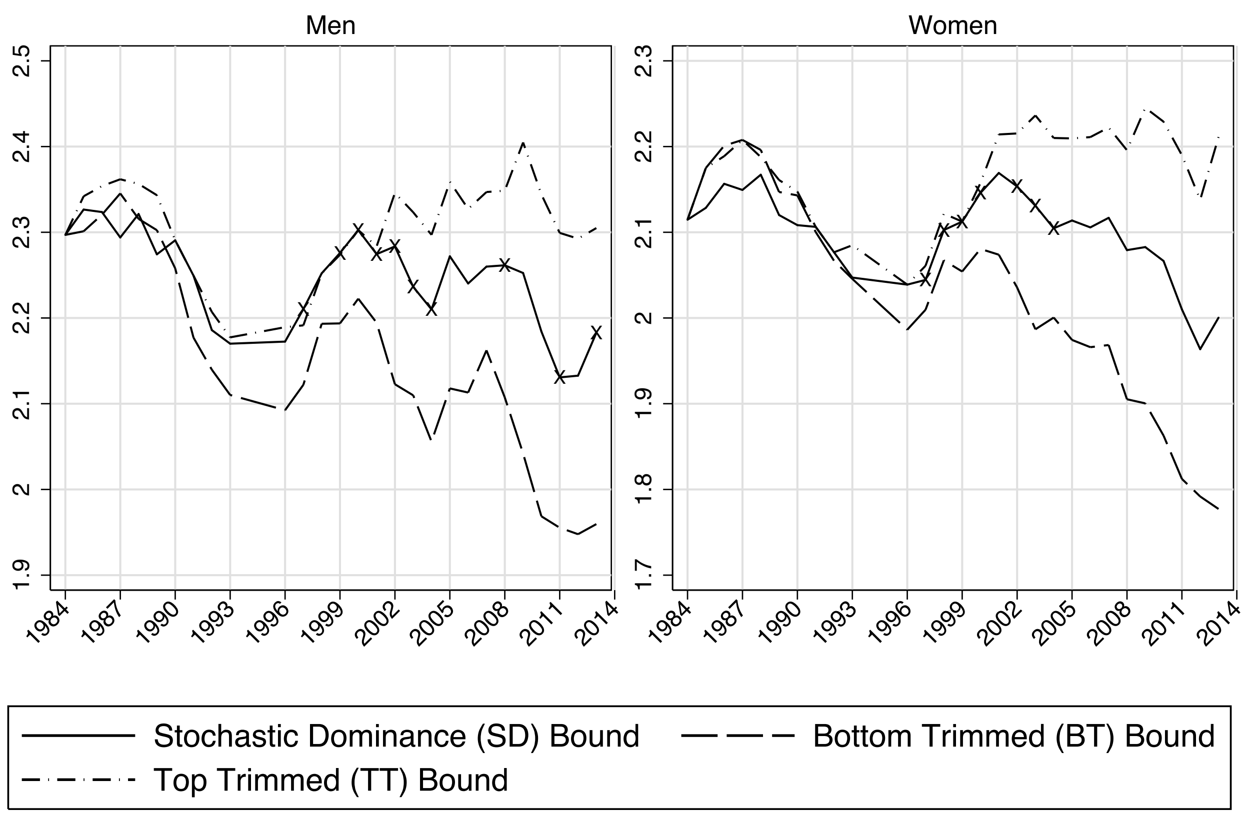

Fig. 12.— Routine Task Price Changes, Young, All Education, Combination Model Trimming

5.2.3. Manual Task Sector

We next turn to bounds on the price for the M sector. With four sectors, the analysis is similar to that in the R sector in the sense that the type of ability distribution model can matter for our bounds. This is seen most clearly in Figure 13, where we plot the bounds with HM trimming. As with the R sector, movements in non-employment imply substantial trimming of the wage distribution after 2008, leading to implied declines in the trimmed sample bound of approximately 100% in five years. These large declines are due to the fact that the Manual sector is relatively small and the movements into unemployment so large that the HM trimming essentially trims the entire sector, leaving us with an identification problem common in the bounding literature where the size of the groups whose wage distribution is unobserved is large relative to the observed group.[24] Thus, we do not plot the T series past 2008 in Figure 13. Prior to 2008, the untrimmed sample bound (the one that relies on the Stochastic Dominance arguments) shows no long term decline for men and only a small decline for women. In both cases, this is a result of declines through the 1980s, increases in the 1990s and a renewal of declines after 2000. For the bound formed with HM model trimming, the trend is reminiscent of what we observed for the R sector, with a ratcheting down in the price across cycles and an ultimate drop between 1984 and 2008 that is on the order of 40%. We present the the interquartile range for this sector in the appendix, where we show that it is essentially flat over the entire period for men and women, implying that the changes plotted in figure 13 correspond to task price changes.

In figure 14, we plot bounds associated with the IS model of ability. For men, both bounds show increases in the 1990s and declines in the 2000s but no long term change between 1984 and 2008. Post 2008, they show about 10% declines. For women, there are strong increases in the 1990s associated with strong growth in employment in this sector (recalling that in the IS model, these additions are assumed to enter at the bottom of the ability distribution) and then declines of just under 10% after 2000. Finally, in figure 15 we plot the bounds implied by the Combination model. As with the results for this model in the Routine sector, both the top and bottom trimmed bounds show strong increases in the 1990s but separate substantially after 2000. For the Manual sector, however, both bounds show the same qualitative picture after 2000: a decline in the Manual sector task price. For the Bottom trimmed bound that decline amounts to between 10 and 20% for both men and women while for the Top trimmed bound it is approximately .3 log points for men and .6 log points for women. Thus, in this case, the model chosen is relevant for determining magnitudes but the direction of the trends in the 1990s and after 2000 is common across the models.

To summarize the results in the figures, in Table 1 we present differences in bounds for five year periods along with associated standard errors for young men of all education groups. In the tables, SD stands for the Stochastic Dominance bounds (i.e., the actual change in the composition constant median wage); HM stands for the trimmed bound from the Hierarchical Model; IS is the

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[24] For example, Blundell et al. (2007) can only identify the upper bound to the median when the less than half of the sample do not have observed wages.

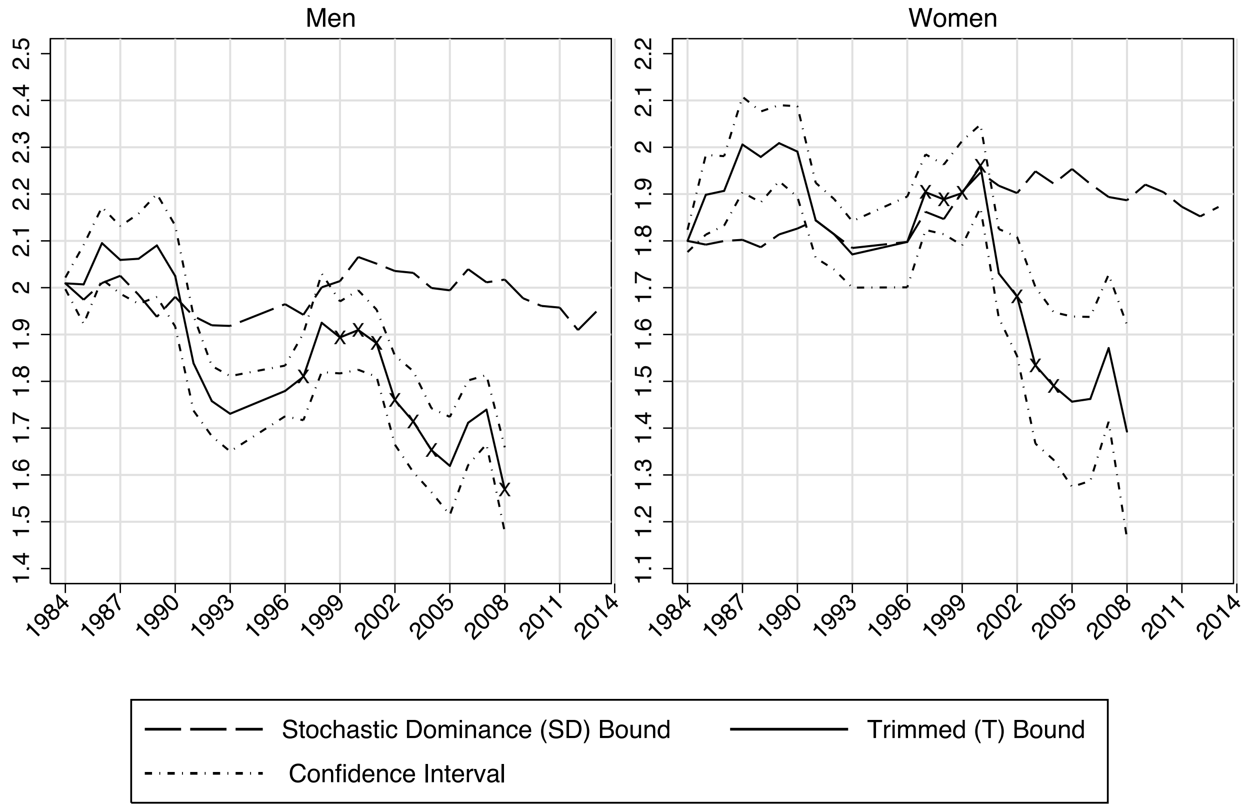

Fig. 13.— Manual Task Price Changes, Young, All Education, HM Trimming

trimmed bound from the Independent Shocks model; and TT and BT correspond to top trimming and bottom trimming, respectively, based on the combination model. Recall that the two bounds are the same under all models for the Cognitive sector. The five year periods necessarily miss some important inflection points observed in the figures but they do allow for a summary of broad patterns. Most notably, the task prices in all sectors rise (and by about the same amount) in the second half of the 1990s, suggesting a general increase in the demand for labour. Once those changes are combined with the more substantial declines in Routine task prices in the early 90s, though, the standard observation of a polarization in task price changes re-emerges for the decade as a whole. For the 2000s, the task prices fall nearly universally, including for the Cognitive sector. The Routine prices fall more than for the other two sectors in some models but this is not universally true and a conclusion that there is ongoing polarization seems to us to be over-ridden by the stronger conclusion that task prices in all sectors declined after 2000. The fact that this is observed in the bounds under all the selection models we considered indicates that this is a robust conclusion.

In Figure 16, we use the HM model to present the implied ability shifts in each sector, relative

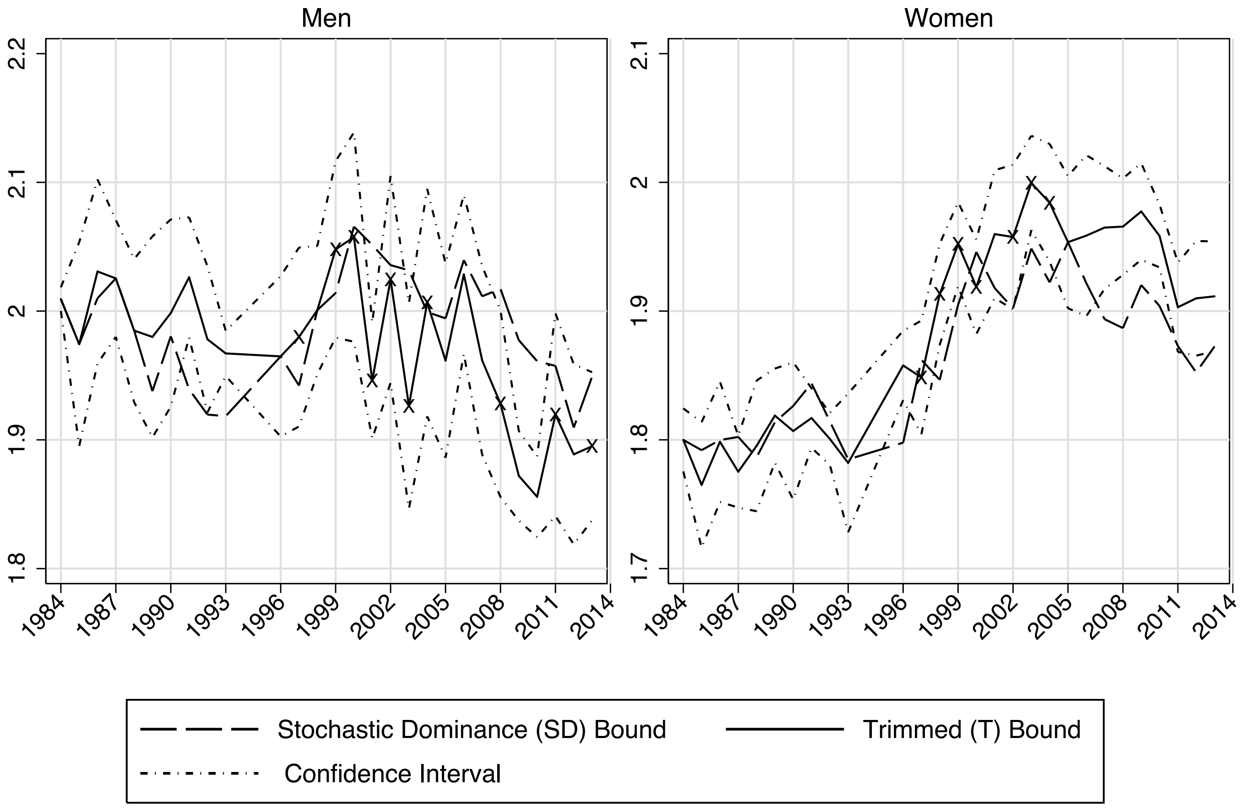

Fig. 14.— Manual Task Price Changes, Young, All Education, IS Trimming

to 1984. In particular, in this figure, we plot the difference between the SD and T series. This creates an index, normalized to zero in 1984, of maximum relative ability shifts in each sector under the single ability model. When this index is positive, relative ability in the sector is greater than in 1984 under any selection pattern other than the one which defines the Stochastic Dominance bound. This, in turn, implies that observed wages will be higher than an ability-constant wage under any selection scheme other than the SD bound. Similarly, when this index is negative, ability in the sector is lower than in 1984 under almost all selection schemes. The height of the shaded area indicates the maximum possible extent of ability differences (i.e., the one where there is the most extreme selection – captured in the T bound – and the least – captured in the SD bound). For example, in the late 1990s, the cognitive sector grew in size, drawing in lower ability workers. Thus, in Figure 7, the SD line lays below the T line, and the relative ability index in Figure 16 is negative. The magnitude indicates that, in the extreme, median wages in the cognitive sector were about 7 percent lower due to selection than had ability remained at its 1984 levels. For men in the R and M sectors, the index turns positive after about 1990 and remains positive throughout the remainder

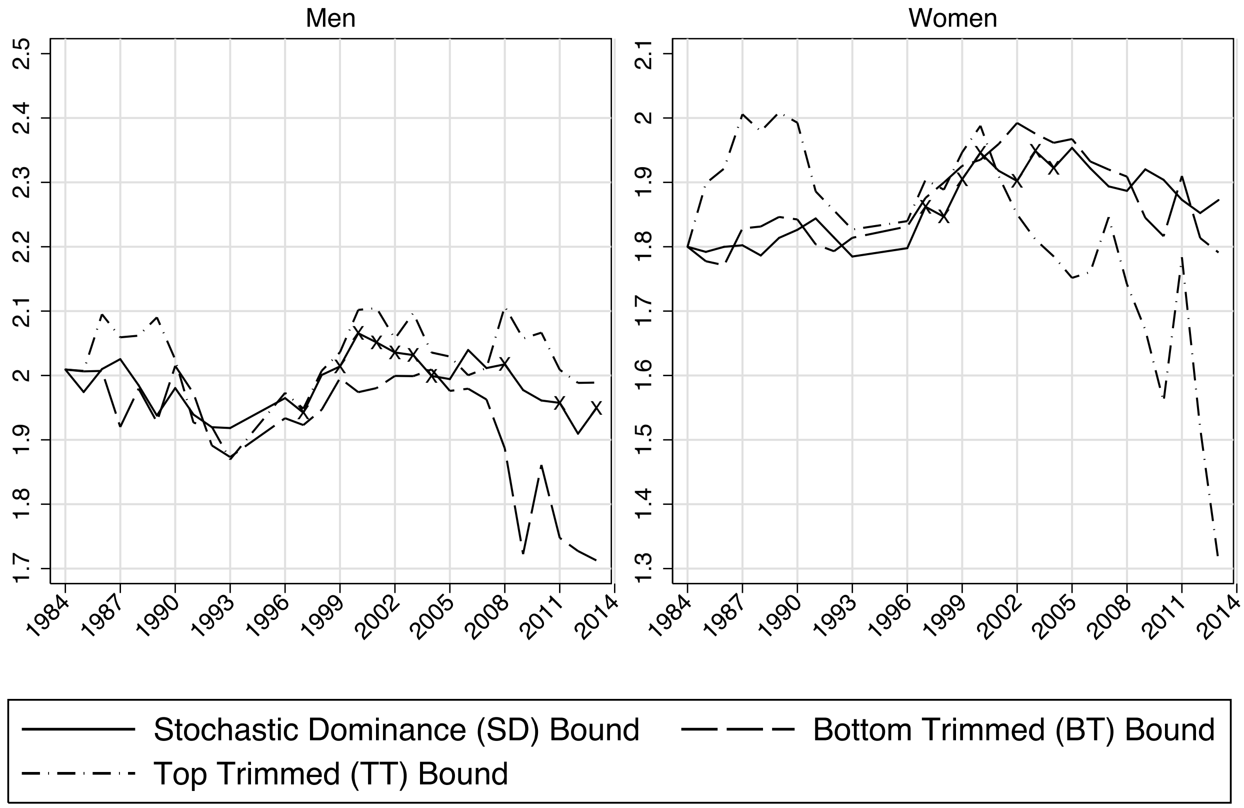

Fig. 15.— Manual Task Price Changes, Young, All Education, Combination Model Trimming

of the series with larger magnitudes after 2000. This indicates that ability has been rising in these sectors, relative to 1984, as these sectors have been shrinking in size and, in the HM model, it is the least-able individuals who have been exiting. For women, the index in the M and R sectors turn positive after 2000, when Figure 6 shows a sudden upturn in growth in the non-employment sector. This figure shows the importance of accounting for shifts in workers' abilities in each sector over time; particularly after 2000, when there is large movements of workers to the home sector.

6. Discussion and Conclusion

The bounds we have constructed indicate that taking account of changes in both observable and unobservable characteristic changes can substantially alter our picture of relevant factor price changes for the U.S. in the last thirty years. Simple median wages in both the Cognitive (C) and Manual (M) sectors rise strongly through the 1990s and then rise more slowly after 2000, while Routine (R) sector wages fall for men over the same period but rise in much the same way as M

Table 1: Implications for Men

	Cognitive		Routine					Manual				
	SD	*HM*	*SD*	*HM*	*IS*	*TT*	*BT*	*SD*	*HM*	*IS*	*TT*	*BT*
1990-1985	-0.042	-0.023	-0.036	-0.051	-0.039	-0.051	-0.043	0.0062	0.018	0.024	0.018	0.0085
se	0.026	0.046	0.018	0.026	0.026	0.026	0.027	0.015	0.070	0.055	0.068	0.070
1996-1990	-0.11	-0.14	-0.12	-0.20	-0.18	-0.10	-0.17	-0.016	-0.25	-0.034	-0.052	-0.081
se	0.024	0.051	0.012	0.025	0.028	0.031	0.035	0.020	0.062	0.049	0.063	0.053
2000-1996	0.12	0.20	0.13	0.17	0.12	0.11	0.13	0.10	0.13	0.095	0.13	0.040
se	0.025	0.058	0.0075	0.029	0.030	0.036	0.037	0.031	0.051	0.052	0.054	0.035
2005-2000	-0.026	-0.10	-0.031	-0.13	-0.10	0.056	-0.10	-0.071	-0.29	-0.098	-0.073	0.0020
se	0.026	0.065	0.015	0.041	0.032	0.042	0.031	0.036	0.069	0.057	0.057	0.062
2010-2005	0.013	-0.069	-0.088	-0.23	-0.16	-0.015	-0.15	-0.033	-	-0.11	0.037	-0.12
se	0.021	0.067	0.030	0.049	0.040	0.043	0.039	0.026	-	0.042	0.65	0.32

sector wages for women. Taken together, the male wages, in particular, fit with arguments that the U.S. has experienced wage polarization in recent decades.

However, working from versions of a standard Roy model, we argue that the composition of workers within sectors both in terms of observables (because of substantial changes in the education and age distributions for the working age population over time) and unobservables (because of potential selection effects related to the changes in the sizes of the sectors) has shifted in this period. Those shifts, in turn, imply that changes in unconditional observed median wages within sectors may be poor measures of the changes in task prices we ultimately care about. Indeed, once we account for changes in the age and education composition, median wages in all three sectors decline after 2000.

Following Manski (1990) and recent papers such as Lee (2009) and Blundell et al. (2007), we address potential selection on unobservables effects through a bounding exercise. We appeal to the basic logic of Roy models to help in tightening those bounds, showing that the relevant bounds vary depending on whether one assumes that sectoral ability follows: an Hierarchical Model (HM), where the best worker in one sector is also the best in others; an Independent Shocks (IS) model, where worker sectoral abilities are independent across sectors; or a Combination model that incorporates elements of both. We show that the bounds for the change in the task price for the Cognitive sector are the same under all three models, and that given the basic logic of the Roy model, one bound is simply the change in the median wage adjusted for observable composition shifts. The other bound corresponds to trimming a number of observations equal to the change in the size of the C sector from the bottom of the wage distribution and then obtaining the median. Both bounds indicate a pattern of a strongly rising cognitive task price in the 1990s followed by a declining task price in the 2000s, with the bound arising from the trimming exercise showing both large increases in the 90s and larger declines in the 2000s. Thus, our results imply that the increases and then decreases in the cognitive task price is at least as large as the observed change in the median cognitive wage holding the composition in terms of observables constant.

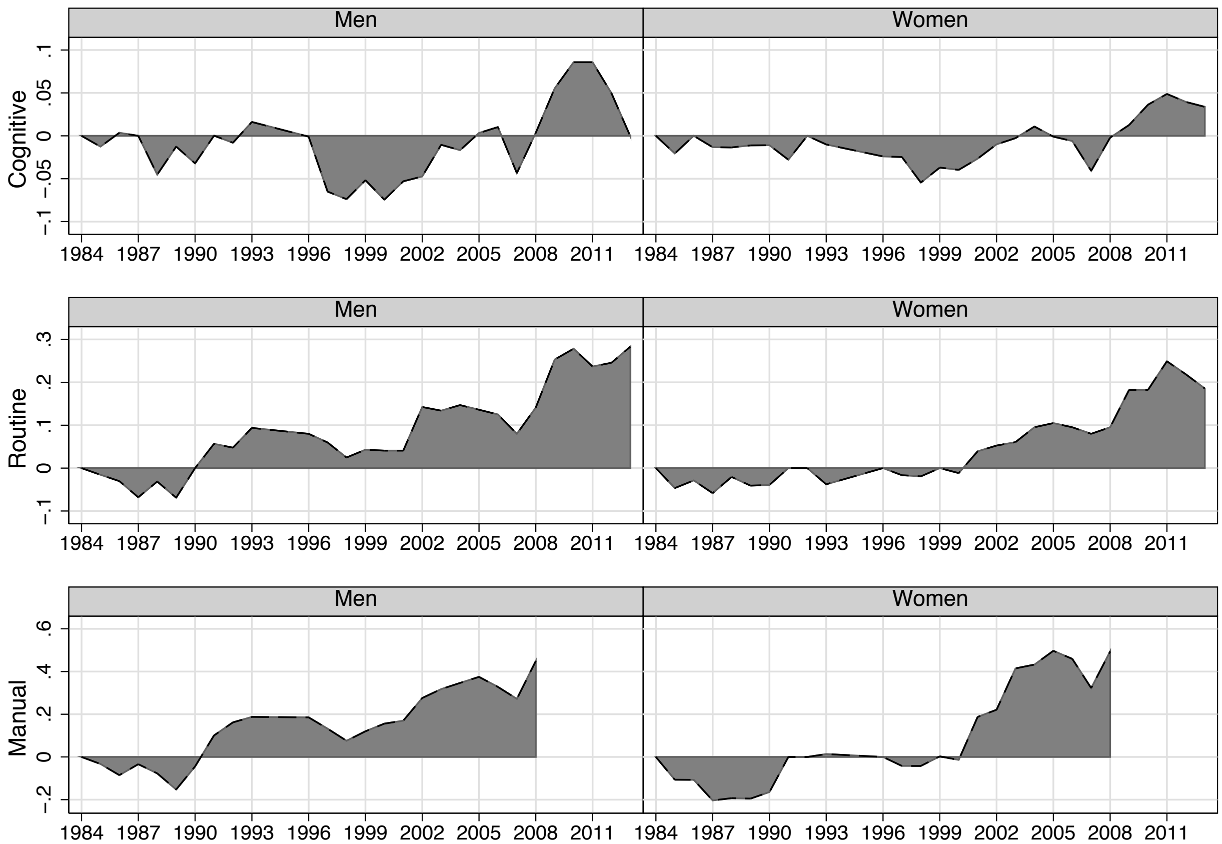

Fig. 16.— Implied Ability Shifts by Sector, All Education, HM Trimming

For the R and M sectors, the different assumptions on the underlying ability distributions has an impact on the bounds. But for the M sector, the differences have to do with magnitudes rather than directions of trends. Under all the models, the M sector task price rose in the 1990s but declined in the 2000s. The R sector task price generally follows the same pattern, though under one extreme bound its trend is simply flat after 2000 rather than declining. The general agreement among the bounds formed under the different selection models indicates that our conclusions are robust.

Overall, we have shown that correcting for selection on observables and unobservables does not change the predominant view that task prices polarized in the US in the 1990s. However, after 2000, examining unconditional median wages for the main task sectors yields very different conclusions from what we reach once we address composition and selection changes. Once we control for selection on observables, by reweighting, and unoservables by bounding we find that the predominant pattern is a decline in task prices in all sectors after 2000 rather than continued polarization.

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– Appendix –

A. A Model of Implicit Contracts with Trending Productivity

In this section, we outline a simple theory of wage determination under implicit contracts with trending task prices. In thinking about what wage measure to use in our bounding exercise, we are influenced by the literature suggesting that implicit contract considerations are important for understanding wage movements (e.g. Beaudry and DiNardo (1995); Ham and Reilly (2002)). Much of that literature works with a stationary macro environment, whereas we are interested in examining trends. For that reason, our implicit contract model is set within a stochastic trend as a framework.

Begin by considering firms and workers in sector, k. Firms hire workers, indexed by j, with output generated by a specific worker given by,

$$z_{kjt} = \eta_{kj} \cdot \exp(e_{kjt}) \tag{A1}$$

That is, a worker has a time invariant component of sector specific productivity given by η_{kj} and an idiosyncratic component, $\exp(e_{kjt})$. The two components are independent across workers and of each other for the same worker. The idiosyncratic component is drawn from a distribution with $E(\exp(e_{kjt})) = 1$.

The value of marginal product of the worker is given by,

$$\Phi_{jkt} = p_{kt} z_{kjt} \tag{A2}$$

where, p_{kt} is the price of output in sector k, movements in which will partly reflect sector wide productivity shocks. In what follows, we will interpret z_{kjt} as the amount of the sector specific task that worker j supplies to sector k (expressed in units of output) and will refer to p_{kt} as the task price. For the purposes of the current discussion, we assume that the task price has a stochastic trend (though, in our estimation, we do not impose any assumption about the form of any trend in the price):

$$p_{kt} = p_{kt-1} + \xi_{kt} \tag{A3}$$

where ξ_{kt} is a disturbance that is independent over time and with respect to the other random variables in the model.

To keep the discussion as simple as possible, we will assume that contracts are fully enforceable and that jobs are infinitely lived apart from the fact that workers die with probability $1 - \delta$ in any period. Workers inelastically supply a fixed number of hours of work per period and have utility equal to the log of their wage. There is free entry of firms so that the present value of profits is driven to zero. Firms and workers face a common discount factor, β.

The solution to the contract involving worker j in sector k and starting in period t_0 is the solution to the problem:

$$\max_{w_{kjt}} \sum_{\tau=0}^{\infty} (\beta\delta)^t \, E_{t_0}[\ln w_{kjt_0+\tau}] \tag{A4}$$

st.

$$\sum_{\tau=0}^{\infty} (\beta\delta)^t E_{t_0}[w_{kjt_0+\tau}] = \sum_{\tau=0}^{\infty} (\beta\delta)^t E_{t_0}[p_{kt_0+\tau}\eta_{kj} \cdot \exp(e_{kjt_0+\tau})]$$

where, E_{t_0} refers to expectations with respect to information available at time, t_0.

The solution to this problem is a fixed wage for all future periods for person j in sector k given by:

$$w_{kjt,t_0} = \eta_{kj} p_{kt_0}, \forall t > t_0 \tag{A5}$$

Several points follow from this result. First, while every person starting a job in period t_0 has a sector k potential wage given by (A5), only workers for whom this wage is better than their alternatives in other sectors will actually be observed with a sector k wage. Thus, the observed average wage for individuals starting a job in sector k in period 0 is given by,

$$E(w_{kjt,t_0} | D_{jkt_0} = 1) = p_{kt_0} E(\eta_{kj} | D_{jkt_0} = 1) \tag{A6}$$

where, D_{jkt_0} is a dummy variable equalling 1 if person j starts a job in sector k in period t_0. Based on this equation, one can see that the average starting wage in a sector will potentially move both because of movements in the task price and because of changes in the composition of who works in the sector.

Holding the selection issues aside for the moment, the other main issue arising from (A5) is that the overall average wage in a sector at a point in time will reflect a weighted average of previous period sectoral productivity shocks. In particular, assume for simplicity that only workers of type l^* choose to work in sector k. Then the average sector k log wage in period t_1 would be given by (again, ignoring any other selectivity),

$$\ln \bar{w}_{kt_1} = (1-\delta) \sum_{\tau=0}^{\infty} \delta^{\tau} \ln w_{l^* t_1, t_1-\tau} \tag{A7}$$

$$= \ln \eta_{kl^*} + \ln p_{kt_1} - (1-\delta) \sum_{\tau=0}^{\infty} \delta^{\tau} \sum_{m=0}^{\tau} \xi_{k,t-m}$$

where, we have assumed that a set of measure 1 of workers enter employment in the sector in each period so that at time t_1 there will be $\frac{1}{(1-\delta)}$ workers alive.[25] The key point is that the wage reflects an average of past productivity shocks with declining weights for periods farther in the past. The difference in average wages between periods t_1 and t_2 would then equal $\ln p_{kt_2} - \ln p_{kt_1}$ plus a term

[25] Note that if we allow for L task types and allow for workers of any task type to be employed in sector k then the

reflecting the fact that different weights would be put on the past shocks in the average wage for each period. This is true even in our simple specification with a constant death rate of workers. In a more realistic scenario with different rates of entry to and exit from jobs over time because of macro events, the weighting put on past shocks could be even more different in any two periods.

While the latter point is straightforward (and follows simply from assuming an implicit contract framework) it is important in helping to determine how we approach trying to isolate movements in the task price. In particular, one potential approach to the selection problem described earlier is to use panel data and follow individual workers in sector k through time. Since this would, by definition, imply following a set of workers with time invariant ability held constant, the resulting changes should capture changes in the task price. This is the approach taken in Cortes (2012). However, in the implicit contract model used here, we would see zero change in wages for a given set of workers even though there are productivity differences driving differences in wages across new entrant cohorts. Simply following average wages in an occupations combines this "stickiness" problem with the selection problem described earlier.

The alternative we pursue in this paper is to examine the wages of new job entrants. Using equation (A5), we can write the difference in the average log wage between new entrants in two periods as,

$$\begin{aligned} E(\ln w_{kjt_1,t_1}|D_{jkt_1}=1) - E(\ln w_{jt_0,t_0}|D_{jkt_0}=1) &= \ln p_{t_1} - \ln p_{t_0} \\ &+ E(\ln \eta_{kj}|D_{jkt_1}=1) - E(\ln \eta_{kj}|D_{jkt_0}=1) \end{aligned} \tag{A9}$$

Thus, examining differences in new entrant wages allows us to focus on contemporaneous movements in task prices but still involves a problem in terms of changes in selection over time.[26] We address the latter through a combination of re-weighting and bounding techniques.

Finally, it is worth noting that in a spot market model, log wages for a worker will equal,

$$\ln w_{kjt} = \ln p_{kt} + \ln \eta_{kj} + e_{kjt} \tag{A10}$$

average wage at a point in time would be,

$$\ln \bar{w}_{kt_1} = (1-\delta)\sum_{\tau=0}^{\infty}\delta^{\tau}\sum_{l=1}^{L}\ln w_{lt_1,t_1-\tau}\cdot\pi_{kl}(t_1,t_1-\tau) \tag{A8}$$

where $\pi_{kl}(t_1, t_1-\tau)$ is the proportion of the employed workers in sector k who started working in period $t_1-\tau$ and are still working in period t_1 who are of type l.

[26] Our approach is similar in spirit to Heckman et al. (1998) and Bowlus and Robinson (2012) both of whom generate skill price series using older workers (who are on a flat portion of the wage-experience profile). While they work across cohorts at an older age, we do the same for new entrants. In the context of their life-cycle human capital model, we would need to add to the identifying assumptions listed below, the assumption that the proportion of time a worker devotes to human capital at the start of his or her working life is invariant to the current task prices.

In that case, following new entrant wages will still capture contemporaneous movements in the task price but will again reflect selection effects that need to be addressed. Thus, the results we provide are of interest under the alternative assumption that wages are set in a spot market.

B. Data

B.1. ORG Current Population Survey

We use the Current Population Survey's Merged Outgoing Rotation Group (ORG) data from 1984-2013, downloaded from the NBER[27]

- Initial extractions included all individuals between the ages of 18-64 inclusive.
- Potential experience calculated as:
    1. age - 23 if college graduate,
    2. age - 15 if post graduate,
    3. int(age - years of school - 6 if some post secondary,
    4. age - 19 if high school graduate,
    5. age - 17 if high school drop out
- Sample further restricted to those with positive potential experience.
- When we focus on our sample of job entrants, we use workers with no more than 5 years of potential experience.
- Prior to 1992, education was reported as the number of completed years. In 1992 and after, education is reported in categories as the highest grade/degree completed.
    1. We convert categories to years of completed school in the post-1991 data based on Park (1994)
    2. We convert years into categories in the pre-1992 data based on Jaeger and Page (1996) (code provided by NBER).

B.1.1. Wage data

The construction of our wage data closely follows Lemieux (2006).

[27] Links are http://www.nber.org/data/cps_may.html and http://www.nber.org/data/morg.html

- Wage data is based on those who report employment in reference week.
- In all wage calculations, we set allocated wages to missing.
- Our hourly wage measure is based on reported hourly wage for those who report hourly payment and not adjusted for topcoding. For workers who are not paid hourly:
  1. We use edited weekly earnings. For the years 1984-1986, we use unedited earnings due to the higher topcode value.
  2. Adjust topcoded wages by a factor of 1.4.
  3. Divide the result by usual hours worked per week.

We argue that younger workers' wages are better measured than older workers and may better approximate competitive outcomes. Table A1 reports that younger workers (age 18-30) are less likely to have allocated or top coded wages, belong to a union or work in the government sector, while being more likely to be paid by the hour.

Table A1: Characteristics of Young vs Older workers

	(1) Allocated Wage	(2) Union	(3) Paid Hourly	(4) Top Coded	(5) Government
Men, Age 18-30	21.0	11.5	68.7	0.23	8.63
Men, Age 31-45	22.7	19.3	52.2	1.61	15.0
Men, Age 46-65	28.1	24.2	48.4	2.48	20.3
Women, Age 18-30	19.1	7.85	68.4	0.066	12.0
Women, Age 31-45	21.4	13.6	59.5	0.35	21.0
Women, Age 46-65	25.7	16.7	58.0	0.36	25.8

Notes: MORG data, 1990-2000, Employed workers only. Each entry indicates the percent of workers in each category.

B.2. Occupation Codes

- The occupation categories we use are based on the 1980/90 Census occupation categories. Several small changes where made in the 1990 Census occupation classifications that required slight aggregation. We use the code provide by http://www.unionstats.com to make these adjustments.
- The categories are consistent from 1983-2002.
- For years after 2002, we must use a crosswalk to allocate workers to 1980/90 categories. To do so, we exploit the fact that between 2000-2002, the Outgoing rotation group has occupations that are dual coded in 1980/90 and Census 2000 schemes. We create crosswalks by calculating

the fraction of each 1980/90 codes that are split across a 2000 code. Using these fractions, we randomly assign an observation a 1980/90 code in the post-2002 data based on that observation's 2000 code and the likelihood given by our crosswalks.

- An alternative is to use the BLS crosswalks[28] to allocated workers to the 1980/90 categories. Our results are robust to either method.
- Our broad occupation categories are made after converting all data to the 80/90 categories and aggregating up. In our main empirical work, we use three occupation groups which we refer to as Cognitive, Routine, and Manual jobs, based on Acemoglu and Autor (2011)'s classifications were they define job categories by their predominant task usage.

C. Additional Figures

In Figure A1, we present the same plot but restrict the sample to those with a college or higher education. Thus, in this figure, we are controlling for both experience and education. The patterns for both males and females are similar to the all-education plot but, in both cases, show larger movements. For example, for males, the bound obtained by trimming at the bottom end increases by over 20% in the 1990s and then declines by more than that in the 2000s. The similarity of the two figures is reassuring in that it suggests a common trend for the task price whether we control for covariates through an averaging approach or by examining one covariate group. In this figure, the X's correspond to years with similar proportions of young people with a college degree or higher – the years within the bands in Figure 1. Again, they indicate that focussing on education constant periods still allows us to conclude that the cognitive task price underwent a major trend change around 2000.

[28]Obtained from http://usa.ipums.org/usa/volii/occ_ind.shtml

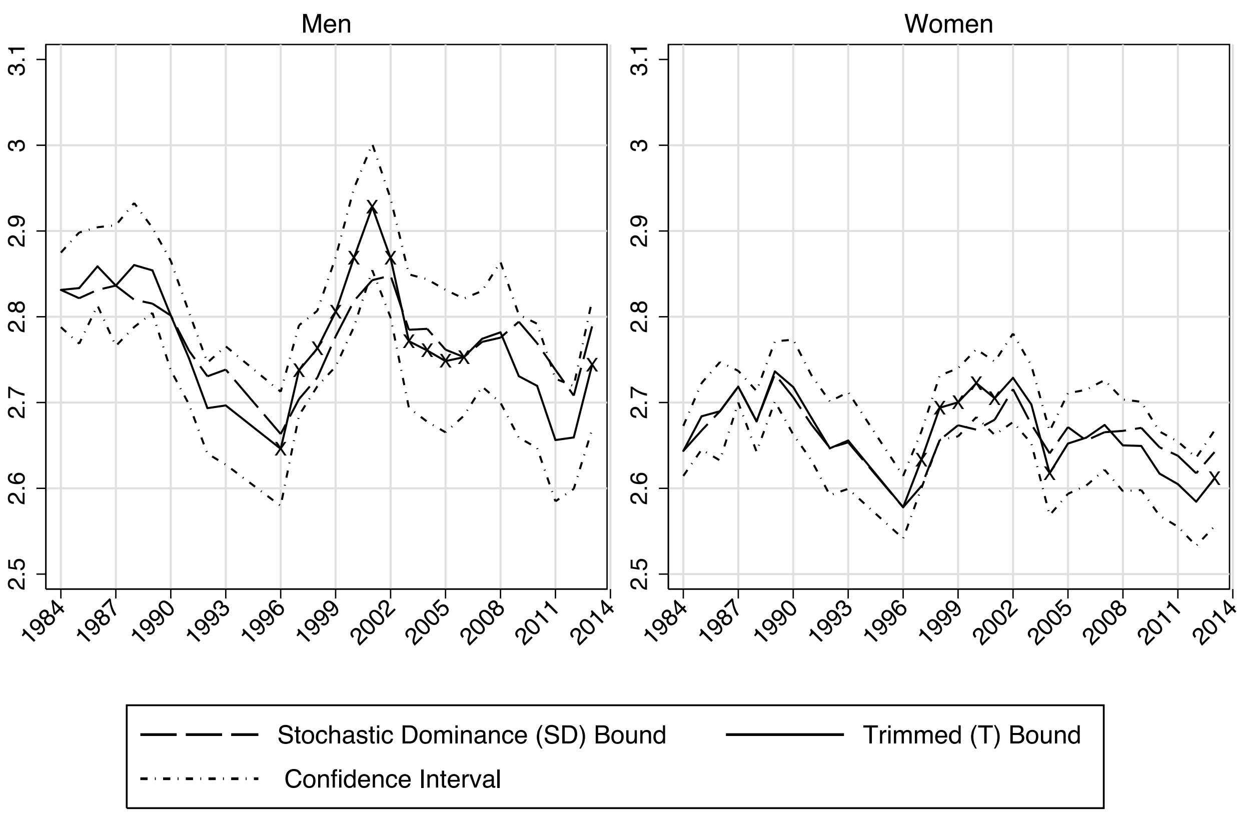

Fig. A1.— Cognitive Task Price Changes, Young, High Education

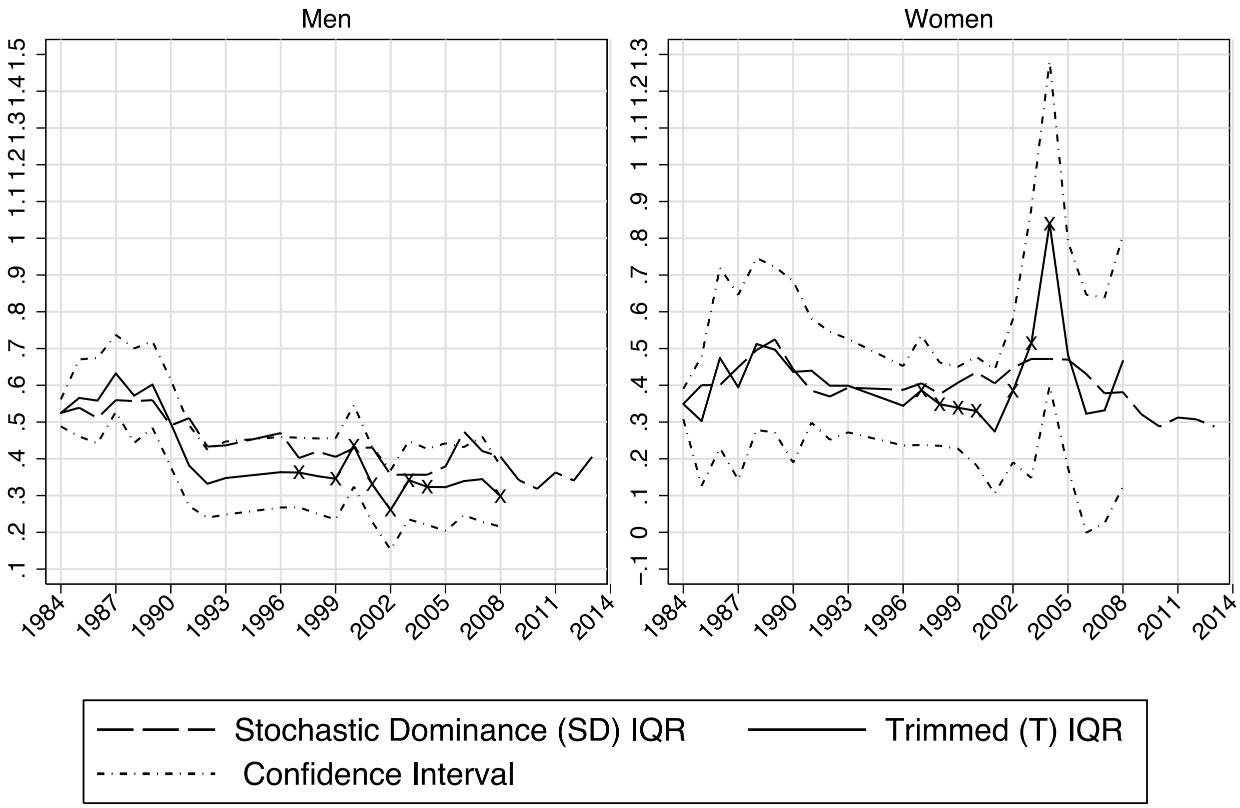

Fig. A2.— Interquartile Range for Manual Task Price Changes, Young, High Education