Rising Wage Inequality: Technological Change and Search Frictions

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Abstract

I investigate whether changes to labor market frictions can explain rising wage inequality in the US. I combine the production framework in Krusell et al. (2000), which emphasizes capital skill complementarity as an explanation for rising wage inequality, with the sequential auction search model of Postel-Vinay and Robin (2002). The presence of search frictions, and hence monopsonistic power, provides a range of explanations for rising wage inequality not present in competitive models i.e. changes to job flows, firm heterogeneity or bargaining power. I find that differences in search frictions between skilled and unskilled workers can explain the presence of a positive skill premium but not its growth. Estimates of capital-skill complementarity in Krusell et al. (2000) are therefore robust to including search frictions.

Keywords: Search Frictions, Monopsony, Labor Markets, Wage Inequality, Technological Change.

1. Introduction

This paper develops a structural model featuring capital skill complementarity and search frictions to asses whether changes to search frictions provide an alternative explanation for increasing wage inequality to the traditional technological explanations emphasized in the literature.[1] Including search frictions as a potential explanation for rising wage inequality is motivated by a number of empirical explanations that, while suggestive of some degree of monopsony power, have so far not been grounded in theory. For example, the importance of firm heterogeneity in explaining growing wage inequality found in Song et al. (2015) or Card et al. (2013) would be difficult to incorporate in a perfectly competitive model where workers would instantly relocate to more productive firms. Similarly the quantitative importance of institutions such as the minimum wage and trade unions for explaining the rise in wage inequality, as documented in Card and DiNardo (2002) and Lee (1999), is difficult to reconcile with perfectly competitive models (see Flinn (2006), Manning (2003) and Teulings (2000)).

I therefore relax the assumption of perfect competition between employers, which runs through much of the literature that seeks to explain the rise in US wage inequality over the last four decades. This assumption is present both in relatively early studies such as Katz and Murphy (1992) and later contributions such as Krusell et al. (2000) and Acemoglu and Autor (2011). A competitive labor market framework, while restrictive in some dimensions, does not preclude a rich variety of explanations for the rise in wage inequality; ranging from the capital-skill complementarity channel in Krusell et al. (2000) to cohort specific supply changes emphasized in Card and Lemieux (2001). However, in a competitive framework these explanations are naturally restricted to two broad categories: those based on technological change; and those based on changes to the skill distribution of workers.

A key contribution of this paper is to develop a structural model that can incorporate both technological and supply based explanations for rising wage inequality and explanations reflecting labor market frictions and institutional change as outlined above. Specifically, I do this by combining the production framework specified in Krusell et al. (2000) with the sequential auction wage bargaining model developed in Postel-Vinay and Robin (2002) and Cahuc et al. (2006). Both frameworks have been very influential in explaining different dimensions of inequality: dynamics of inequality *between* different skill groups in the case of Krusell et al. (2000) and cross-sectional levels of inequality *within* given skill groups in the case of Postel-Vinay and Robin (2002) and Cahuc et al. (2006). Marrying the two frameworks has value for a number of reasons, not least that they touch on issues where there is a great deal of overlap e.g. capital skill complementarity may have

[1] For example, Katz and Murphy (1992), Krusell et al. (2000), and Acemoglu and Autor (2011).

both increased wages of high skilled workers directly, by raising their marginal product of labor, and indirectly by inducing greater vacancy creation for skilled workers thereby lowering the search frictions they face.

Krusell et al. (2000) relate the rise in the graduate wage premium to the fall in the price of capital equipment. They show that a production function where skilled and unskilled labor combine with capital to produce output can provide an explanation for the rise in the graduate wage premium when capital is more complementary with skilled than unskilled labor. Quantitatively, the authors show that this capital skill complementarity channel, when combined with the large falls in the price of capital equipment observed in the data, is able to explain almost all of the rise in the graduate wage premium seen over the 1980s and early 1990s. One contribution of this paper is to update the sample used in Krusell et al. (2000) and show that their parsimonious model continues to provide a good fit to the data.

In the sequential auction model of the labor market in Cahuc et al. (2006), average wages of a given skill type of worker depend on the worker's marginal productivity at a given firm, as in the competitive framework, but also on job contact rates, bargaining strength, the distribution of match quality and outside options in unemployment. The empirical part of my paper focuses on the contribution of changes to job contact rates and to the distribution of match quality to the rise in the graduate wage premium, and examines whether the estimates of capital skill complementarity from Krusell et al. (2000) are materially different once these factors are accounted for. This could be the case if, for example, job market frictions have significantly worsened for unskilled workers relative to skilled. This would mean my model, because it allows for these change of frictions, would be less reliant on the technology channel emphasized in Krusell et al. (2000) to explain the growth in the graduate wage premium, and so would deliver parameter estimates suggesting a smaller degree of capital skill complementarity.

This could have important consequences both for understanding the evolution of skill premiums and for policy; the technological explanation for the rise in the skill premium implies governments face a relatively acute trade-off if they wish to boost living standards of low skill workers through policies such as the minimum wage or increasing unionization rates. On the one hand such policies can improve the incomes of those in work but, if low skilled labor is significantly substitutable with capital, these policies risk pushing more workers into unemployment. Any findings suggesting a lower level of substitutability between unskilled labor and capital will therefore have an important bearing on how acute this trade-off is.

My strategy for taking the model to the data has been to maintain consistency with Krusell et al. (2000) by focusing on the graduate wage premium as my measure of labor market inequality, and by using data from the U.S National Accounts and the Current Population Survey (CPS). I find that differences in search frictions between graduates and non-graduates can explain the presence of a graduate wage premium due to higher estimated job contact rates and lower job destruction rate for graduates, but cannot explain the growth of the wage premium. I therefore find that estimates of capital-skill complementarity in the production framework of Krusell et al. (2000) are not significantly changed by allowing for labor market frictions.

This finding is driven by the fact that the empirical measures of labor market frictions I use, such as job-to-job mobility and job destruction rates, while favoring skilled workers (graduates) relative to unskilled workers in terms of levels, do not exhibit any time trends favoring skilled workers over the last thirty years. This means they are unable to provide an alternative explanation for the rise in the graduate wage premium. This also suggests that the potential amplification mechanism discussed above - that increased demand for skilled workers raised wages directly via an increase in their productivity and indirectly via a reduction in their search frictions - does not appear to have strong support in the data. The absence of any strong trends in employment transition rates favoring skilled workers means the model is, like that of Krusell et al. (2000), reliant on the capital skill complementarity channel to match the historic rise in the graduate skill premium.

Using the same data sources as Krusell et al. (2000), i.e. National Accounts and employee data from the CPS, prevents identification of bargaining parameters, which are assumed to be constant.[2] So while the theoretical framework I present allows changes to bargaining strength as a potential explanation for the increase in the skill premium, I do not investigate this empirically.

The rest of this paper is organized as follows. Section 2 will present the model, starting first with an overview of Krusell et al. (2000) (henceforth KORV) before explaining how I incorporate search frictions and wage bargaining as per Cahuc et al. (2006) into the production environment in KORV. Section 3 discusses the data I use to estimate the combined model, before Section 4 presents my econometric approach. Section 5 presents findings and Section 6 concludes.

2. The Model

Introducing search frictions and wage bargaining into the production technology in KORV presents a key theoretical challenge: doing so directly would mean firms bargaining with many workers i.e. a multi-player game as per Stole and Zwiebel (1996). These multi-player games seem unlikely to be relevant for considering

[2]Identification of bargaining parameters in search models typically relies on the presence of matched employer-employee data, as is the case in Cahuc et al. (2006)

aggregate dynamics in the labor market. I therefore abstract from such effects by specifying a competitive final good firm, where production is as in KORV, and an intermediate good sector with a labor market structure identical to the sequential auction model of Cahuc et al. (2006) i.e. with random search by unemployed and employed workers, firm heterogeneity, and where incumbent employers can respond to job offers made to their employees by rivals. There are segmented intermediate goods sectors for unskilled and skilled labor, and firms within each intermediate goods sector have heterogeneous quality.

I will first present an overview of the KORV model in its original form, before explaining how I incorporate intermediate goods sectors with search frictions into the KORV production environment. Finally, I explain how search frictions and wage bargaining operate within the intermediate goods sector.

2.1. **KORV Production Function: No Frictions or Intermediate Goods.** In the original formulation of KORV, final good in period t, Y_t is produced using capital structures, $K_{st,t}$, capital equipment, $K_{eq,t}$, and skilled and unskilled labor, S_t & U_t, as inputs, as shown in equation (1).

$$\begin{aligned} Y_t &= A_t G(K_{st,t}, K_{eq,t}, U_t, S_t) \\ &= A_t K_{st,t}^{\alpha}[\mu U_t^{\sigma} + (1-\mu)(\lambda K_{eq,t}^{\gamma} + (1-\lambda)S_t^{\gamma})^{\frac{\sigma}{\gamma}}]^{\frac{1-\alpha}{\sigma}} \end{aligned} \tag{1}$$

with $\sigma, \gamma < 1$ and $\alpha, \lambda, \mu \in (0,1)$. The elasticity of substitution between unskilled labor input and capital equipment, denoted by $\varepsilon_{u,k_{eq}}$, is equal to $1/(1-\sigma)$. The elasticity of substitution between unskilled and skilled labor inputs, denoted $\varepsilon_{u,s}$, is also equal to $1/(1-\sigma)$. Finally, the elasticity of substitution between the skilled labor input and capital equipment, denoted by $\varepsilon_{s,k_{eq}}$, is equal to $1/(1-\gamma)$. Capital-skill complementarity is present if and only if $\sigma > \gamma$. The parameter, α, together with λ, determine the capital share of output, and μ determines the output share of unskilled workers.

Unskilled and skilled labor input are hours worked by non-graduates and graduates in efficiency units e.g $U_t \equiv \Psi_{u,t}h_{u,t}$, $S_t \equiv \Psi_{s,t}h_{s,t}$, where $\Psi_{i,t}$ is the efficiency of labor input of skill type $i \in \{u, s\}$, and $h_{i,t}$ is the total amount of hours worked by that skill type. Krusell et al. (2000), in their baseline model, impose that $\Psi_{u,t}$ and $\Psi_{s,t}$ both follow stationary stochastic processes. They do not allow for any time trend in relative labour efficiency as this would introduce an unexplained source of skills-biased technical change, contrary to the aim of their paper which is to examine the contribution of increased capital use to the rise in the graduate wage premium.

The final good is used for consumption c_t, investment in capital equipment $x_{eq,t}$ and investment in capital structures $x_{st,t}$, as shown in equation (2), where q_t is the relative efficiency of producing capital equipment from the final good (or equivalently $1/q_t$ is the relative price of capital equipment).

$$Y_t = c_t + x_{st,t} + \frac{x_{eq,t}}{q_t} \tag{2}$$

The final good producer has the following profit maximisation problem, where $(w_{u,t}, w_{s,t})$ denote the wages for unskilled and skilled workers respectively, and $(r_{st,t}, r_{eq,t})$ denote the rental rates for capital structures and equipment respectively:

$$\begin{aligned}\max_{K_{st,t},K_{eq,t},h_{u,t},h_{s,t}} \Pi = {} & A_t K_{st,t}^{\alpha}[\mu U_t^{\sigma} + (1-\mu)(\lambda K_{eq,t}^{\gamma} + (1-\lambda)S_t^{\gamma})^{\frac{\sigma}{\gamma}}]^{\frac{1-\alpha}{\sigma}} \\ & - w_{u,t}h_{u,t} - w_{s,t}h_{s,t} - r_{st,t}K_{st,t} - r_{eq,t}K_{eq,t}\end{aligned} \tag{3}$$

In both KORV's original model and in my adaptation the final good producer is assumed to be competitive, so the first order conditions (FOCs) for its profit maximisation problem are as shown in equations (4) through (7).

$$\begin{aligned}
w_{u,t} &= A_t(1-\alpha)K_{st,t}^{\alpha}[\mu U_t^{\sigma} + (1-\mu)(\lambda K_{eq,t}^{\gamma} + (1-\lambda)S_t^{\gamma})^{\frac{\sigma}{\gamma}}]^{\frac{1-\alpha-\sigma}{\sigma}} && (4)\\
&\quad \times \mu U^{\sigma-1}\Psi_{u,t} \\
w_{s,t} &= A_t(1-\alpha)K_{st,t}^{\alpha}[\mu U_t^{\sigma} + (1-\mu)(\lambda K_{eq,t}^{\gamma} + (1-\lambda)S_t^{\gamma})^{\frac{\sigma}{\gamma}}]^{\frac{1-\alpha-\sigma}{\sigma}} && (5)\\
&\quad \times(1-\mu)(\lambda K_{eq,t}^{\gamma} + (1-\lambda)S_t^{\gamma})^{\frac{\sigma-\gamma}{\gamma}}(1-\lambda)S_t^{\gamma-1}\Psi_{s,t} \\
r_{eq,t} &= A_t(1-\alpha)K_{st,t}^{\alpha}[\mu U_t^{\sigma} + (1-\mu)(\lambda K_{eq,t}^{\gamma} + (1-\lambda)S_t^{\gamma})^{\frac{\sigma}{\gamma}}]^{\frac{1-\alpha-\sigma}{\sigma}} && (6)\\
&\quad \times(1-\mu)(\lambda K_{eq,t}^{\gamma} + (1-\lambda)S_t^{\gamma})^{\frac{\sigma-\gamma}{\gamma}}K_{eq,t}^{\gamma-1} \\
r_{st,t} &= \alpha A_t K_{st,t}^{\alpha-1}[\mu U_t^{\sigma} + (1-\mu)(\lambda K_{eq,t}^{\gamma} + (1-\lambda)S_t^{\gamma})^{\frac{\sigma}{\gamma}}]^{\frac{1-\alpha}{\sigma}} && (7)
\end{aligned}$$

In the absence of frictions, growth in the graduate wage premium (denoted by $\pi_t = w_{s,t}/w_{u,t}$) is given in equation (8), where g_z denotes the growth rate in variable z.[3]

$$\begin{aligned} g_{\pi_t} \simeq {} & (1-\sigma)(g_{h_{u,t}} - g_{h_{s,t}}) + \sigma(g_{\Psi_{s,t}} - g_{\Psi_{u,t}}) + \\ & (\sigma-\gamma)\lambda\Big(\frac{K_{eq,t}}{S_t}\Big)(g_{K_{eq,t}} - g_{\Psi_{s,t}} - g_{h_{s,t}})\end{aligned} \tag{8}$$

2.2. **KORV production function: Incorporating Intermediate Goods.** I incorporate search frictions into the model by introducing two segmented intermediate goods sectors that employ unskilled and skilled workers respectively, with the sector and corresponding skill group indexed by $i \in \{u, s\}$. I now interpret U_t and S_t as the effective amount of intermediate goods produced in the unskilled and skilled intermediate goods sectors respectively. Specifically I define $U_t \equiv \Psi_{u,t} y_{u_t}$

[3]This by derived by taking logs of the graduate wage premium - given by the final goods firm's FOCs - and then differentiating with respect to time to give equation (8).

and $S_t \equiv \Psi_{s,t} y_{s_t}$ where $y_{i,t}$ is the volume of intermediate goods produced in skill sector i and $\Psi_{i,t}$ is, analogously to the original KORV environment, the efficiency level of that intermediate good.

In each segmented intermediate goods market, unemployed workers are randomly matched to intermediate firms of quality ν (I refer to this as match quality), and with a sampling distribution $F_{i,t}(\nu)$ and pdf, $f_{i,t}(\nu)$. I denote the cdf and pdf of the cross-section distribution of match quality across all employed workers as $L_{i,t}(\nu)$ and $l_{i,t}(\nu)$, which differs from the sampling distribution as workers can search for higher quality matches on the job.

A worker in a match of quality ν produces exactly ν units of intermediate good for every hour they work, though hours worked are assumed to be fixed within each skill type of worker i.e. hours do not vary with match quality.[4] The effective input of intermediate goods from the unskilled and skilled intermediate sectors are therefore as shown in equation (9), where $h_{i,t}$ is again the raw total amount of hours worked by workers of skill type i.

(9)

$$U_t \equiv \Psi_{u,t} y_{u,t} = \Psi_{u,t} h_{u,t} \int_{\nu_{inf,u}}^{\nu_{max}} \nu \ell_{t,u}(\nu) d\nu \,,\; S_t \equiv \Psi_{s,t} y_{s,t} = \Psi_{s,t} h_{s,t} \int_{\nu_{inf,s}}^{\nu_{max}} \nu \ell_{t,s}(\nu) d\nu$$

Final good producers are again assumed to be competitive and so pay a price, p_i, for a unit of type i intermediate good given by $p_i = \frac{\partial Y}{\partial y_i}$. An intermediate good firm of match quality ν in intermediate sector i receives revenue equal to $p_i \nu$. The following subsection describes how search frictions and wage bargaining operates within the intermediate goods sectors.

2.3. **Intermediate Goods Sectors.** All intermediate firms and workers have common discount rate, ρ, and are risk neutral. As is standard in the search literature, I assume firms can employ a maximum of one worker so intermediate firms become synonymous to matches or jobs. Job destruction rates are exogenously given, but allowed to vary by skill sectors and are denoted by $\delta_{i,t}$. Workers receive flow income in unemployment equal to $b_{i,t} * p_{i,t}$, where $b_{i,t}$ is their replacement rate and $p_{i,t}$ is the price of the intermediate good they produce as defined above.[5]

The job offer arrival rates in unemployment and employment are denoted $\lambda_{0,i,t}$,$\lambda_{1,i,t}$ and will be assumed to be exogenously given.

[4] I make this assumption to maintain consistency with the original formulation of the KORV production function where labor inputs are measured in efficiency units of total hours worked.

[5] This implies that unemployment income is independent of the match quality that the worker had in their previous employment. Re-employment wages are therefore not path dependent, which aids tractability in the model - see Cahuc et al. (2006) for further discussion.

Intermediate Goods Sector: Wage Bargaining with Unemployed Workers

Equation (10) represents the Bellman equation for an unemployed worker of skill type i, where $V_{0,i}(p_i)$ is the expected lifetime utility of an unemployed worker, $\phi_0(p_i, \nu)$ is the wage paid to a previously unemployed worker now in a match of quality ν and $V(p_i, \phi_0(p_i, \nu), \nu)$ is the expected lifetime utility of that worker.

$$(\rho + \lambda_{0,i}) V_{0,i}(p_i) = p_i b_i + \lambda_{0,i} \int_{\nu_{inf_i}}^{\nu_{\max}} V(p_i, \phi_0(p_i, x), x)\, dF_i(x) \tag{10}$$

Unemployed workers receive flow income $b_i p_i$ in the current period and in the next period, which is discounted at rate ρ, they encounter a match with probability $\lambda_{0,i}$, where the match quality is drawn from the distribution $F_i(\nu)$ and lies in the interval $[\nu_{inf_i}, \nu_{max}]$.

As in Cahuc et al. (2006), I assume that there is a latent vacancy posting cost, which ensures that intermediate firms won't post a match unless it will be accepted by a worker, so the lower bound of the match quality distribution is the workers reservation match quality ν_{inf_i}.

Cahuc et al. (2006) propose a generalized form of Nash bargaining both for unemployed and employed workers. Previously unemployed workers ('entrant' workers) are paid a wage, $\phi_0(p_i, \nu)$, that equalizes the expected lifetime utility of working at a match of quality ν with the expected lifetime utility of being unemployed plus a share, β (the bargaining parameter), of match surplus $V(p_i, p_i\nu, \nu) - V_{0,i}(p_i)$, as expressed in equation (11).[6]

$$V(p_i, \phi_0(p_i, \nu), \nu) = V_{0,i}(p_i) + \beta\left[V(p_i, p_i\nu, \nu) - V_{0,i}(p_i)\right] \tag{11}$$

From equations (11) and (10), Cahuc et al. (2006) derive the closed form solution for entrant wages shown in equation (12), where $\bar{F} \equiv 1 - F$.

$$\phi_0(p_i, \nu) = p_i \cdot \left(\nu_{inf_i} - (1-\beta) \int_{\nu_{inf_i}}^{\nu} \frac{\rho + \delta + \lambda_1 \bar{F}_i(x)}{\rho + \delta + \lambda_1 \beta \bar{F}_i(x)} dx\right) \tag{12}$$

Note that Cahuc et al. (2006) also use equation (11) and 10 to derive the expression for the reservation match quality, ν_{inf_i}, shown in equation (13).

$$\nu_{inf_i} = b_i + \int_{\nu_{inf_i}}^{\nu_{max}} \frac{\beta(\lambda_{0,i} - \lambda_{1,i})\bar{F}_i(x)}{\rho + \delta_i + \beta_i \lambda_{1,i} \bar{F}_i(x)} dx \tag{13}$$

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[6] I have assumed there is zero value to a firm from having a vacancy i.e. a free entry condition holds, which when combined with the assumption of a common discount rate for firms and workers and risk neutrality of all agents means the match surplus can be expressed as $V(p_i, p_i\nu, \nu) - V_{0,i}(p_i)$ i.e. the match surplus equals the worker surplus when they are paid a wage equal to their marginal product.

Intermediate Goods Sectors: Wage Bargaining with Employed Workers

A key novelty in the sequential auction model of Cahuc et al. (2006) is that incumbent employers can respond to rival job offers made to their employees, in contrast to wage posting models such as Burdett and Mortensen (1998). In this environment, the wage paid to an employee will depend on (i) the match quality of the highest ranked match they have encountered in their employment spell, ν^+, which will be at their current employer, (ii) the match quality at their outside option, ν^-, which is the second highest match they have encountered in their employment spell, and (iii) the price of the intermediate good they produce, p_i, which will be the same for all workers in a given skill group i . I denote this wage $\phi(p_i, \nu^-, \nu^+)$.

Suppose a worker employed at a match of quality ν encounters a match of quality ν', and is currently paid a wage w. If $\nu' > \nu$, the employee moves to higher quality match and gets wage $\phi(p_i, \nu, \nu')$. Encountering a match of quality $\nu' < \nu$ will trigger a renegotiation of the employees wage contract at their current employer if ν' exceeds a threshold, denoted $\chi(p_i, w, \nu)$, where $\chi(p_i, w, \nu)$ is defined by the equality $\phi(p_i, \chi(p_i, w, \nu), \nu) = w$.

The Bellman equation for a worker of skill type i employed at a match of quality ν and paid a wage w is shown in equation (14).

$$\begin{aligned}
&\left[\rho + \delta_i + \lambda_{1,i}\bar{F}_i(\chi(p_i, w, \nu))\right] V_i(p_i, w, \nu) \\
&= w + \delta_i V_{0,i}(p_i) + \lambda_{1,i} \int_{\chi(p_i,w,\nu)}^{\nu} V_i(p_i, \phi(p_i, x, \nu), x) dF_i(x) \\
&+\lambda_{1,i} \int_{\nu}^{\nu_{\max}} V_i(p_i, \phi(p_i, \nu, x), x) dF_i(x) \qquad (14)
\end{aligned}$$

The worker, after receiving wage w in the current period, will either lose their job with probability δ_i or, failing that, make contact with a match that triggers a renegotiation of their wage in the next period with probability $\lambda_{1,i}\bar{F}_i(\chi(p_i, w, \nu))$. If the match quality at the alternative match, x, lies in the region $(\chi(p_i, w, \nu), \nu]$ the worker stays at their current employer and receives a pay rise $\phi(p_i, x, \nu) - w$. If $x > \nu$ the worker moves to the alternative match and gets a wage $\phi(p_i, \nu, x)$. Note that this wage need not be greater than their previous wage as workers may be willing to take a pay cut if the possibility of future wage increases at the higher quality match is sufficiently greater than at their incumbent employer.

Equation (15) shows the result of the wage bargaining that occurs when an employee encounters a match of sufficient quality to trigger a wage renegotiation. I denote the higher of the incumbent and rival employer's match quality as ν^+ , and the lower match quality as ν^-. The worker will supply their labor to the higher quality match, and the lower quality match becomes their outside option. Cahuc et al. (2006) adapt the Nash bargaining game of Osborne and Rubinstein (1990) to an environment with rival bidders, and show the bargained wage must satisfy equation (15).

$$V(p_i, \phi(p_i, \nu^-, \nu^+), \nu^+) = V(p_i, p_i\nu^-, \nu^-) + \beta[V(p_i, p_i\nu^+, \nu^+) - V(p_i, p_i\nu^-, \nu^-)] \tag{15}$$

The worker receives their outside option, which is the value of working at the firm with productivity ν^- at a wage equal to their marginal product, $p_i\nu^-$, plus a share, β, of the match surplus from working at the higher productivity firm.

Cahuc et al. (2006) prove that the wage, $\phi(p_i, \nu^-, \nu^+)$, satisfying equation (15) has the form shown in equation (16) when value functions are as defined as in equation (14).

$$\phi(p_i, \nu^-, \nu^+) = p_i\left(\nu^+ - (1-\beta)\int_{\nu^-}^{\nu^+} \frac{\rho + \delta + \lambda_1\bar{F}(x)}{\rho + \delta + \lambda_1\beta\bar{F}(x)}dx\right) \tag{16}$$

Intermediate Goods Sectors: Wage and Employment Distributions

The key objects of interest in the model are the wage distributions for each skill type of worker. The analysis of the preceding sections indicates that a worker's wage depends on two stochastic variables: their current match quality, ν, and that of their outside option, χ. As in Cahuc et al. (2006), I impose that the labor market is in steady state in order to derive expressions for the cross section distributions of ν, $L_i(\nu)$, and of χ conditional on ν, $L_i(\chi|\nu)$.

Steady state in the labor market requires equations (17) through to (19) to hold (where e_i^{ue} denotes the unemployment rate of skill type i, and I have suppressed that there is a total population, N_i, of type i workers that would multiply both sides of each equation).

$$\delta_i(1 - e_i^{ue}) = \lambda_{0,i}e_i^{ue} \tag{17}$$

$$\lambda_{0,i}F_i(\nu)e_i^{ue} = [(\lambda_{1,i}\bar{F}_i(\nu) + \delta_i)](1 - e_i^{ue})L_i(\nu) \tag{18}$$

$$\lambda_{0,i}f(\nu)e_i^{ue} + \lambda_{1,i}L_i(\chi)f(\nu)(1 - e_i^{ue}) = [(\lambda_{1,i}\bar{F}_i(\chi) + \delta_i)]\times (1 - e_i^{ue})L_i(\chi|\nu)\ell_i(\nu) \tag{19}$$

Equation (17) requires that the inflows of workers into unemployment, which is shown in the left hand side (LHS) of the equation, equals the outflow from unemployment which is shown on the right hand side (RHS). Equation (18) requires the inflow (LHS of the equation) into the measure of workers employed at a match of quality less than ν equals the outflow (RHS of the equation): the inflow consists of unemployed workers who make contact with a match of quality less than ν with probability $\lambda_{0,i}F_i(\nu)$, and the outflow is employed workers with match quality below ν who either lose their job with probability δ_i or make contact with a higher quality match with probability $\lambda_{1,i}\bar{F}_i(\nu)$. Finally equation (19) requires that the inflow (LHS of the equation) into the measure of workers employed at a match of quality ν and with an outside option of match quality less than χ equals the outflow (RHS of the equation): the inflow consists of unemployed workers meeting a match of quality ν with probability $\lambda_{0,i}f(\nu)$ (by definition their outside option, i.e. unemployment, has a match quality less than all feasible values of χ), plus workers previously employed at a match of quality less than χ who make contact with a match of quality ν with probability $\lambda_{1,i}L_i(\chi)f(\nu)$; the outflow is employed workers with a match quality equal to ν and with an outside option of match quality less than χ who either lose their job with probability δ_i or receive an offer of a match of quality exceeding χ with probability $\lambda_{1,i}\bar{F}_i(\chi)$.

The expressions for the steady state cross sectional distribution of workers across matches and outside options derived from the steady state requirements above are shown in equations (20) and (21), where $\kappa_{1,i} \equiv \frac{\lambda_{1,i}}{\delta_i}$.

$$L_i(\nu) = \frac{F_i(\nu)}{1 + \kappa_{1,i}\bar{F}_i(\nu)} \tag{20}$$

$$L_i(\chi|\nu) = \left[\frac{1 + \kappa_{1,i}L_i(\chi)}{1 + \kappa_{1,i}L_i(\nu)}\right]^2 \tag{21}$$

The expected wage for a worker of type i is given by:

$$E(w_i) = p_i \int_{\underline{\nu}}^{\nu_{max}} \Bigg[\nu - [1 + \kappa_{1,i}\bar{F}_i(\nu)]^2 \times \int_{\nu_{inf}}^{\nu} \frac{(1-\beta)[1 + \frac{\delta_i}{\delta_i+\rho}\kappa_{1,i}\bar{F}_i(x)]}{[1 + \frac{\delta_i}{\delta_i+\rho}\kappa_{1,i}\beta\bar{F}_i(x)][1 + \kappa_{1,i}\bar{F}_i(x)]^2} dx\Bigg] \ell_i(\nu) d\nu \tag{22}$$

The graduate wage premium in the model ($E(w_s)/E(w_u)$) will therefore depend on the same variables as in Krusell et al. (2000), which influence the price of the intermediate good produced by skill type i, p_i , but also on relative job mobility rates, outside options in unemployment, distributions of match quality, and bargaining strength. In this paper I use the same data as in Krusell et al. (2000) which limits my ability to identify the impact of all these potential channels on the graduate wage premium. I focus on the impact of changes to relative job mobility rates, outside options in unemployment and to the distribution of match quality.

3. Data

This section describes the data I use to estimate the parameters in the KORV production function and in the sequential auction labor markets in the intermediate goods sectors. I then present my estimation approach in detail in Section 4 with identification further examined in Appendix B.

3.1. **Data: Krusell et al. (2000).** In keeping with KORV's original approach, I use labor market data from the Current Population Survey (CPS) and data on capital inputs and the labor share of income from U.S national accounts. Skilled (unskilled) labor is defined as total hours worked by graduates (non-graduates).[7] The authors split each skill type down further into education, gender and race cells to impute hours for those with missing data. I follow their exact approach for comparability.[8]

The authors differentiate between capital equipment, such as machinery, hardware and software, and capital structures e.g. buildings, as capital-skill complementarity is more likely to occur with the former than the latter.[9] An important element of KORV's approach is using a relative price deflator for capital equipment that is based on the approach of Gordon (1990), which they use to calculate the real value of the stock of capital equipment (all other variables are deflated using a GDP deflator). This relative price of equipment falls significantly over KORV's sample period, which in turn implies that the real value of capital equipment used by firms increases appreciably faster than capital structures. Polgreen and Silos (2008) show that use of alternative price series suggest significantly less capital skill complementarity.

The key trends driving results in KORV are summarised in Figure 1. The rise in the graduate wage premium shown in Panel (a) of Figure 1 happens despite the increase in relative supply of skilled labor shown in Panel (b): given the authors assume constant relative labor efficiency in their baseline specification, the only possible driver of the rise in the graduate wage premium is the growing use of capital equipment shown in Panel (c) combined with some degree of capital skill complementarity, which is indeed what their results suggest. The authors estimate

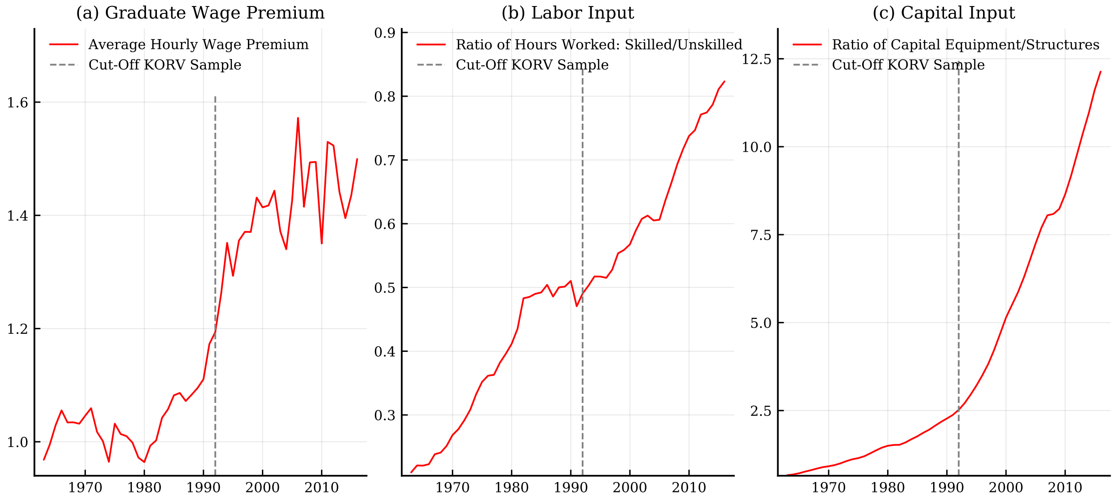
[7]All CPS data is taken from the Integrated Public Use Microdata Series (IPUMS) distribution: https://cps.ipums.org/cps/

[8]See Appendix 1 of Krusell et al. (2000) for details of this approach

[9]The capital stock series are constructed recursively as per Krusell et al. (2000): I use a starting stock of capital equipment and structures in 1963 using data from National Accounts data and add annual investment data in equipment and structures also from the National Accounts. Both investment series are deflated by the non-durable consumption deflator used in DiCecio (2009) (available on the Federal Reserve Bank of St. Louis' Economic Data website (FRED): https://fred.stlouisfed.org/series/CONSDEF). Capital equipment investment is additionally deflated using the relative capital equipment deflator from DiCecio (2009) (also available on FRED: https://fred.stlouisfed.org/series/PERIC), which is based on the approach of Gordon (1990). I apply the same depreciation rates for capital stock as Krusell et al. (2000): 12.5% for equipment and 5% for structures.

an elasticity of substitution between capital equipment and unskilled labor of 1.67 vs an equivalent elasticity of 0.67 for skilled labor.

Figure 1. Key Data Trends in KORV

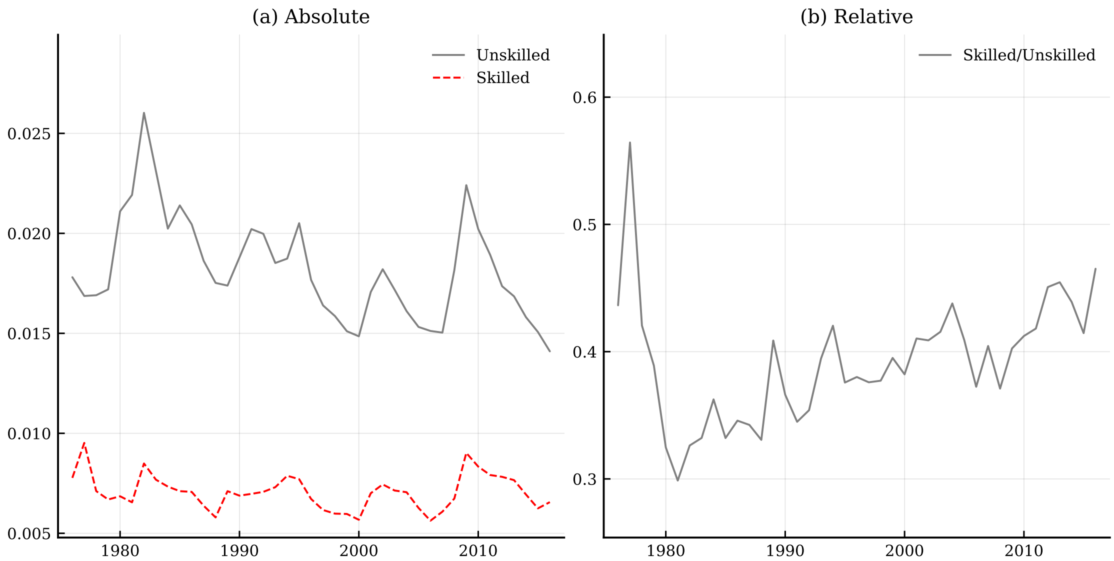


Notes: The grey dashed line in all panels represents the end of the sample period used in Krusell et al. (2000). Wage and hours worked data (shown in panels (a) and (b) respectively) are taken from the Annual Social and Economic (ASEC) Supplement of the CPS, and modified as per Krusell et al. (2000). Panel (c) shows the relative stock of capital equipment to capital structures.

3.2. **Data: Labor Market Frictions.** I supplement the data used by Krusell et al. (2000) with data on labor market frictions, also from the CPS. With each measure of labor market friction, the key dimension of interest will be the time trend in frictions for skilled workers relative to the trend faced by unskilled workers. In the absence of distinct trends in relative frictions it is unlikely that incorporating labor market frictions into KORV will offer a different explanation for the rise in the graduate wage premium than the original KORV specification.

A crucial search friction is the degree of competitive intensity, $\kappa_{1,i}$ which is the rate of job to job contact rates relative to job destruction rates ($\kappa_{1,i} \equiv \frac{\lambda_{1,i}}{\delta_i}$). This determines how quickly workers proceed up the job ladder. I take job destruction rates from the monthly panel element of the CPS, as shown in Figure 2. While skilled workers have lower job destruction rates than unskilled workers in all years, this difference has narrowed over time as unskilled workers' job destruction rates have trended downwards while those of skilled workers have a relatively stable trend.

Figure 2. Job destruction rates



Notes: Job destruction rates are the average monthly transition rates of workers from employment to unemployment for a given year. Panel (a) shows the series separately for unskilled and skilled workers, Panel (b) shows the series for skilled workers relative to that of unskilled workers. Source: Basic Monthly files of the CPS.

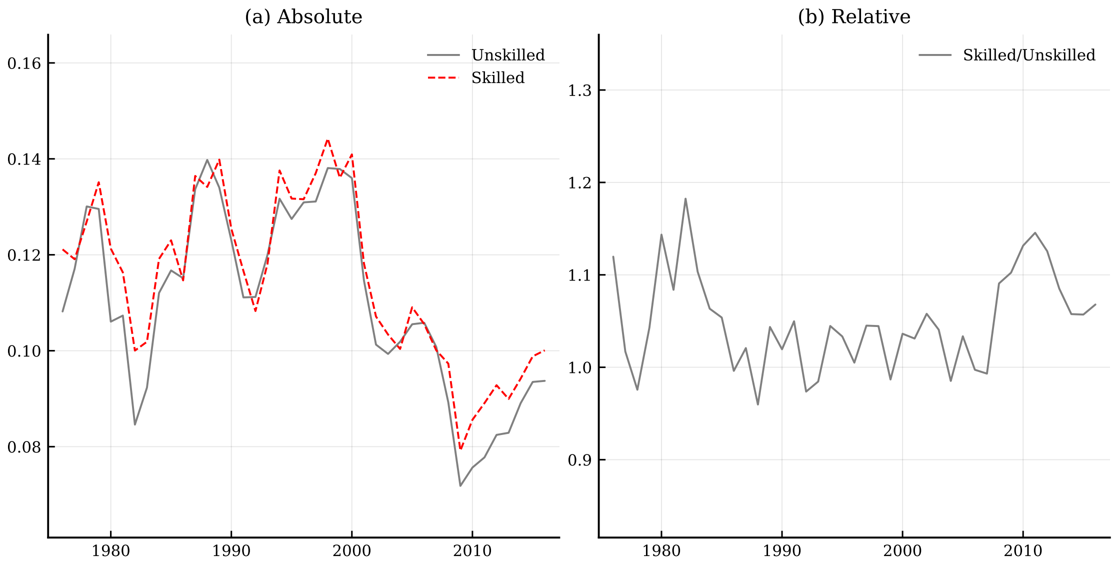
Job contact rates are not readily observable in the CPS and there has only been a question on change of employers since 1994, which hampers comparison with KORV since their original sample period finished in 1992. Since in any case job-to-job transitions would be used to infer job contact rates (not all contacts result in a transition), I use an alternative measure of job mobility which is the proportion of continuously employed individuals that report having at least two non-concurrent employers in the previous year (the 'multiple employer' rate) which is shown in Figure 3. Figure 4 shows that movements in the multiple employer rate track movements to job-to-job mobility rates very closely. [10]

In absolute terms, skilled workers have generally had slightly higher multiple employer rates than unskilled workers. This difference has been broadly stable over time, though it appears to be relatively counter-cyclical. Both job-to-job mobility and multiple employer rates have declined significantly since the early 2000s for skilled and unskilled workers alike.[11]

[10]The CPS question on number of employers in the last year started in 1976.

[11]The aggregate trend of declining job flows is documented in e.g. Decker et al. (2016) and Molloy et al. (2016)

Figure 3. Multiple Employer Rates



Notes: The multiple employer rate is the proportion of workers with no spells of unemployment who have had more than one non-concurrent employer in the previous year. Panel (a) shows the series separately for unskilled and skilled workers, Panel (b) shows the series for skilled workers relative to that of unskilled workers. Source: Annual Social and Economic Supplement of the CPS.

The importance of movements up and down the job ladder for mean wages depends on the dispersion of match quality. I use the standard deviation of log residual wages as a target to identify the distribution of match quality (Section 4 and Appendix B discuss estimation and identification in more detail). I calculate the residual wage after controlling for years of education, race, sex and year in Mincer type wage regression. I do this separately for skilled and unskilled workers. I do not control for age since there are some endogenous returns to job tenure and total employment duration in my model, both of which are correlated with age (and are not directly measured in the CPS over the duration of my sample period).[12] This measure of dispersion increases in relative terms for skilled workers as shown in Figure 5.[13]

Finally the environment workers face in unemployment, both in terms of unemployment flow income and job contact rates, has an impact on the average quality

[12]This risks attributing some variance in wages driven by human capital returns to experience to job ladder effects. However, I find that my estimates of the parameters of the KORV production function do not change if I control for age when calculating residual wage variance - see Appendix C for this and other robustness checks. Nevertheless there may still be some unobservable human capital differences not picked up by either years of education or age that get attributed to job ladder effects using this approach. This represents a disadvantage of

FIGURE 4. Multiple Employer and Job-to-Job Mobility Rates

Notes: The figure compares the multiple employer rate defined in Figure 3 to the average monthly transition rate of employees to new jobs ('Job-to-Job Mobility Rate') from the Basic Monthly files of the CPS. Panel (a) shows this comparison for unskilled workers, Panel (b) shows the comparison for skilled workers. Both series are normalised with reference to their value in 1995.

of matches and wages for employed workers. This impact is less in models with on-the-job search than in models without, but it nonetheless must be accounted for.

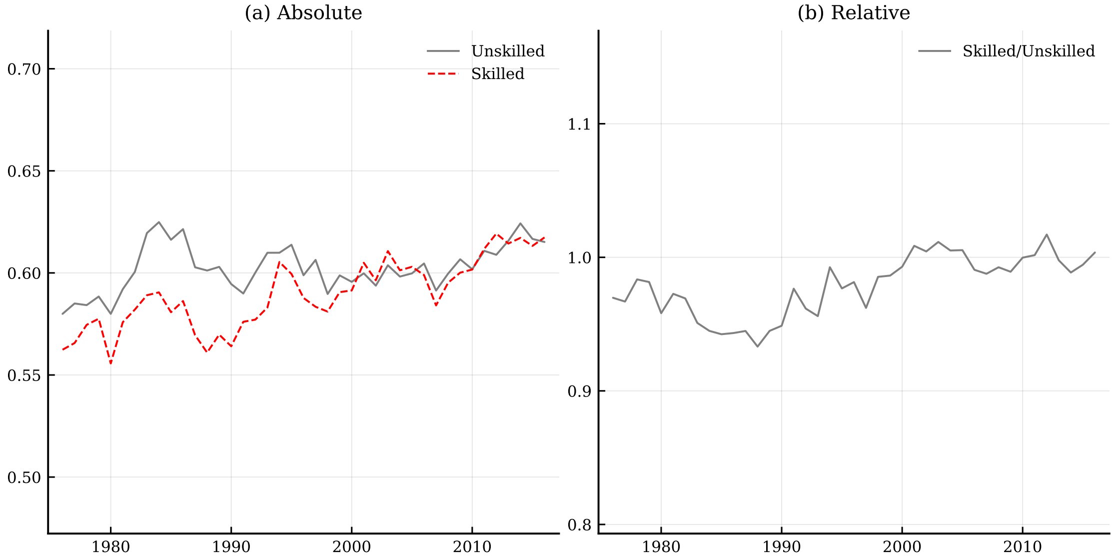
Specifically I will need to estimate or calculate the lower bound of the match quality distribution for each skill type, $\nu_{inf,i}$. In principle, this could be done by exploiting the tractable relationship between the lower bound of the sampling distribution of match quality and unemployment replacement rates and job contact rates shown previously in equation (13).

However, replacement rates are determined not only by legislative framework but also by the degree of insurance provided by asset accumulation, family/social relationships and many other factors beyond this making it difficult to observe in practice. I therefore directly estimate $\nu_{inf,i}$ by targeting the ratio of average wages of workers in the first five percentiles of the wage distribution to the median wage. This empirical moment is shown in Figure 6, where the trends shown suggest

maintaining consistency with KORV by using employee data only rather than using matched employee-employer data to better distinguish worker and firm fixed effects.

[13]Note that using other measures of wage dispersion, such as the interquartile range, does not change my estimates of the KORV production function parameters - see Appendix C.

FIGURE 5. Residual Log Wage Dispersion



Notes: The figure shows the variance of residual log hourly wages from a Mincer wage regression of wages against education, race, sex and year. Hourly wages are again calculated as per Krusell et al. (2000) using ASEC CPS data, but are now trimmed (by dropping hourly wages in the bottom and top percentiles) to minimise measurement error. Panel (a) shows the series separately for unskilled and skilled workers, Panel (b) shows the series for skilled workers relative to that of unskilled workers.

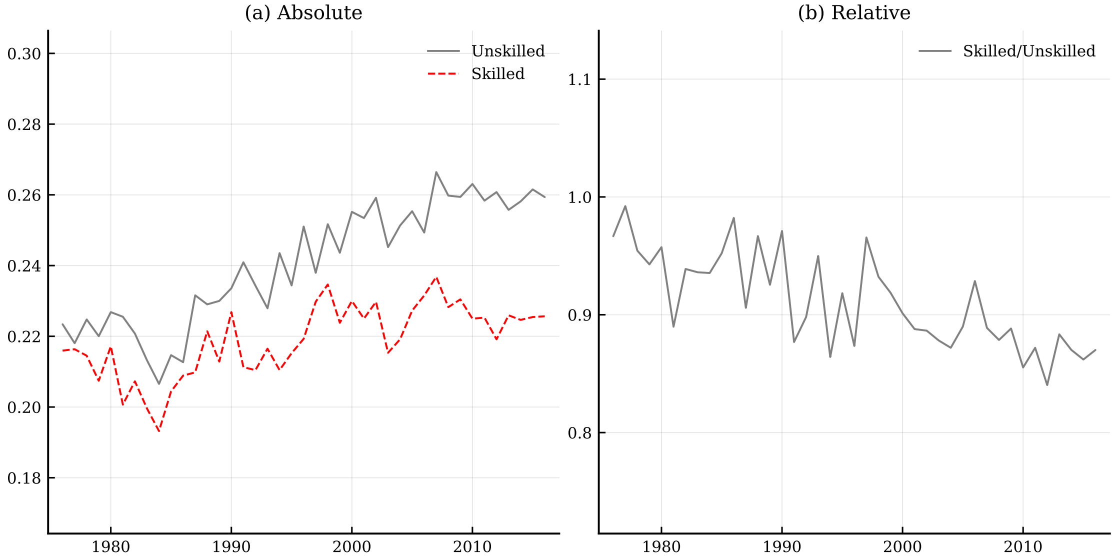
changes to outside options have compressed the tail of the unskilled wage distribution more than for skilled workers.[14]

Note that when I simply replicate KORV's estimation approach I use exactly the same treatment of the data as they do, however when it comes to incorporating frictions I will trim the bottom and top percentile of the wage distribution out of the sample to minimise measurement error, which is more of a concern for estimating the sequential auction part of my model since I target higher order wage moments than when estimating the KORV parameters.

Overall, most of the measures of frictions I consider favour graduates in levels terms, however the most significant time trends are that skilled workers have seen their relative job destruction rates increase and their relative wage dispersion increase. In the context of my model and estimation approach, the latter time trend partially mitigates the former. In particular, we will see that the increase in relative wage dispersion for skilled workers means estimates of the variance parameter

[14]The estimated parameters of the KORV production function are not sensitive to using different measures of the lower bound of the wage distribution i.e. the actual minimum, or different wage percentiles - see Appendix C.

Figure 6. Lower Bound of Wages Relative To Median



Notes: The figure shows the lower bound of the wage distribution (defined as the average wage of workers in the bottom five percentiles of the wage distribution) divided by the median wage. Hourly wages are again calculated as per Krusell et al. (2000) using ASEC CPS data, but are now trimmed (by dropping hourly wages in the bottom and top percentiles) to minimise measurement error. Panel (a) shows the series separately for unskilled and skilled workers, Panel (b) shows the series for skilled workers relative to that of unskilled workers.

of the match quality sampling distribution also increase in relative terms for skilled workers. This leads to a relative increase in the cross sectional average of their match quality and wages.[15]

4. Estimation Approach

As with my exposition of the model, I will first present the original estimation approach used by Krusell et al. (2000), i.e. under perfect competition and with no intermediate goods sectors. I then set-out a two stage strategy for estimating the KORV parameters in the context of my model. The first stage is to estimate the parameters of the sequential auction model in the intermediate goods markets. The second stage is to incorporate results from the first stage to estimate the parameters of the KORV production function in the final good sector.

[15]This is a function of job to job contact rates that significantly exceed job destruction rates in all years, which means that $L_i(\nu)$, the cross-sectional distribution of match quality across employees, will generally first order stochastically dominate $F_i(\nu)$, the sampling distribution. This in turn means a mean preserving increase in the spread of the $F_i(\nu)$ will lead to a increase in the cross sectional mean of match quality.

4.1. **KORV Estimation: Without Frictions.** Krusell et al. (2000) estimate their model by simulated pseudo maximum likelihood (SPML), matching the model's predictions for the labor share of output and the wage bill ratio of skilled workers relative to unskilled workers, denoted lsh_t and wbr_t respectively, to their empirical counterparts.[16] In addition, Krusell et al. (2000) target a no arbitrage condition between capital structures and equipment, i.e. their empirical strategy aims to minimise the difference between the model's predictions for the rate-of-return (RoR) on capital structures and the predicted RoR for capital equipment, alongside the other empirical targets mentioned above.[17] All model moments come from the first order conditions of the final good firm's profit maximisation condition given in equations (4) through (7).This estimation strategy is summarised in equations (23), (24) and (25) respectively, where X_t is the set of factor inputs $(K_{st,t}, K_{eq,t}, U_t, S_t)$, ($\kappa_{eq}$,$\kappa_{st}$) are the depreciation rates for capital equipment and structures respectively, and ϕ is the vector of all parameters to be estimated.

$$\frac{w_{u,t}h_{u,t} + w_{s,t}h_{s,t}}{Y_t} = lsh_t(X_t, \psi_t; \phi) \tag{23}$$

$$\frac{w_{s,t}h_{s,t}}{w_{u,t}h_{u,t}} = wbr_t(X_t, \psi_t; \phi) \tag{24}$$

$$\begin{aligned} 0 &= (1 - \kappa_{st}) + A_{t+1}G_{K_{s,t}}((X_t, \psi_t; \phi) - E_t(\frac{q_t}{q_{t+1}})(1 - \kappa_{eq}) - \\ &q_t A_{t+1} G_{k_{eq,t}}((X_t, \psi_t; \phi) \end{aligned} \tag{25}$$

Equations (23), (24) and (25) can be represented in vector form as $Z_t = f(X_t, \psi_t, \epsilon_t; \phi)$, where Z_t is a vector of the empirical or targeted moments on the left hand side of equations (23), (24) and (25) and $f(X_t, \psi_t, \epsilon_t; \phi)$ is a vector of the model moments on the right hand side of these equations.

Note that there are two stochastic elements in this system of estimation equations. First ψ_t is a (2×1) vector of the log of the efficiency levels of unskilled and skilled labor respectively, and is assumed to follow a stationary process in KORV's benchmark estimation as set out in equation (26).

$$\psi_t = \psi_0 + \omega_t,\ \psi_t \equiv \log .(\Psi_{u,t}, \Psi_{s,t}) \tag{26}$$

[16]SPML is generally attributed to Laroque and Salanie (1993) and is used when a closed form solution for the exact likelihood or quasi likelihood are both unavailable. Just as MLE can be viewed as a specific form of GMM (where the expectation of the score is the relevant moment), so SPML can be viewed as specific form of SMM where I am taking the expectation of a set of moments across both simulations and across time.

[17]This is done as neither RoR is directly observable in the data.

ω_t is a vector shock process to the log of labor efficiency that is assumed to be multivariate normal and *iid* with covariance matrix Ω i.e. $\omega \overset{i.i.d}{\sim} N(0, \Omega)$, and ψ_0 is a vector of the log of initial values of unskilled and skilled labor efficiency $(\psi_{0,u}, \psi_{0,s})$. In the benchmark estimation, the authors impose that there is no covariance between the two labor efficiency shocks and that they have a common variance so Ω can be rewritten as $\Omega = \eta_\omega^2 I$.[18]

The other stochastic process in this estimation procedure is in the no arbitrage condition, equation (25), where the third term on the right hand side of this equation $E_t(\frac{q_t}{q_{t+1}})(1-\kappa_{eq})$ is the undepreciated capital equipment multiplied by the expected rate of change in the relative price of equipment. Krusell et al. (2000) make the simplifying assumption that this term can be replaced with $\frac{q_t}{q_{t+1}}(1 - \kappa_{eq}) + \epsilon_t$, where $\epsilon_t \sim N(0, \eta_{\epsilon_t})$.

In principle, the vector of parameters to be estimated, ϕ, contains 11 elements :$\{\kappa_{st}, \kappa_{eq}, \alpha, \mu, \lambda, \sigma, \gamma, \eta_\varepsilon, \eta_\omega, \psi_{0,u}, \psi_{0,s}\}$. However the authors calibrate $(\kappa_{st}, \kappa_{eq})$ using estimates from the literature, estimate η_ε separately , and normalize $\psi_{0,s} = 0$.[19] This leaves $\phi = \{\alpha, \mu, \lambda, \sigma, \gamma, \eta_\omega, \psi_{0,u}\}$ to be estimated i.e seven parameters: given the estimation approach targets three moments for each year of their 30 year dataset, the model is over-identified.

Finally, the authors construct an instrument for hours worked, $\hat{h}_{u,t}, \hat{h}_{s,t}$ to allow for potential endogeneity between relative hours worked and relative wages.[20] While such endogeneity would be irrelevant if the sole goal was to match the model to the data, instrumenting labor inputs means one can more credibly give the parameters economic interpretations, i.e. as elasticities of substitution, and hence use the model for counter-factual analysis. The exogenous factor inputs used in model estimation are therefore $\hat{X}_t = (K_{st,t}, K_{eq,t}, \hat{h}_{u,t}, \hat{h}_{s,t})$. Estimation then proceeds in three steps:

(1) Draw S values of the vector of shocks to labor efficiency, ω_t^j, and of the forecast error in expected price gains of capital equipment, ϵ_t^j,(where j

[18] As a robustness check, Krusell et al. (2000) do allow for a non-zero covariance between the two efficiency shocks and differing variances, but the estimated covariance is very small and there is little difference between the estimated variances so they opt for a benchmark estimation with zero covariance and a common variance.

[19] The authors set $\kappa_{eq} = 0.125$ and $\kappa_{st} = 0.05$ following Greenwood et al. (1997) and estimate η_ε via an ARMA regression of q_t.

[20] The instruments are constructed by regressing hours worked of each skill type against a constant, current, and lagged stock of capital equipment and structures, the lagged relative price of equipment, a trend, and the lagged value of the U.S. business cycle indicator produced by the Economic Cycle Research Institute: https://www.businesscycle.com/ecri-reports-indexes/all-indexes.

indexes the realization of the shock) to get S realizations of $f(\hat{X}_t, \psi_t^j, \epsilon_t^j; \phi)$ from the model for each time period t,

(2) Use these S realizations to obtain the following moments:

$$m_s(\hat{X}_t, \phi) = \frac{1}{S}\sum_{i=1}^{S} f(\hat{X}_t, \psi_t^j, \epsilon_t^j; \phi)$$

$$V_s(\hat{X}_t, \phi) = \frac{1}{S-1}\sum_{i=1}^{S}(f(\hat{X}_t, \psi_t^j, \epsilon_t^j; \phi) - m_s(\hat{X}_t, \phi))(f(\hat{X}_t, \psi_t^j, \epsilon_t^j; \phi) - m_s(\hat{X}_t, \phi))'$$

(3) Minimise the following objective function:

$$\begin{aligned} l_s(\hat{X}_t, \phi) = & \frac{1}{2T}\sum_{t=1}^{T}\Big\{(Z_t - m_s(\hat{X}_t, \phi))'(V_s(\hat{X}_t, \phi))^{-1} \\ & \times (Z_t - m_s(\hat{X}_t, \phi)) + \log(\det(V_s(\hat{X}_t, \phi)))\Big\} \end{aligned} \tag{27}$$

In a companion paper to Krusell et al. (2000), Ohanian et al. (1997) look at how successfully the estimation approach above identifies the true parameters of the model in Monte Carlo simulations, and find very small median and mean biases in estimators even when using relatively few simulations in estimation i.e. for $S = 10$. They find that for $S = 50$ the mean bias is "essentially zero".

4.2. **Incorporating Frictions into KORV Estimation.** I proceed in two steps to incorporate the sequential auction model of Cahuc et al. (2006) into estimation of the KORV production function parameters. First I separately estimate the parameters of the sequential auction model, which include job contact rates for employed workers of each skill type $\lambda_{1,i,t}$ and the parameters of their match distribution. Appendix B examines identification of these parameters in greater detail, showing exact identification of the job contact rates using the empirical strategy outlined here and providing evidence from Monte Carlo simulations that my strategy for estimating the parameters of the match quality distribution also successfully identifies the true parameters of the model.

In the second part of my estimation approach, I estimate the parameters of the KORV production function incorporating the changes to labor market frictions implied by the first stage of my estimation process. This second step is, in econometric terms, a minor modification of the original approach of Krusell et al. (2000), as presented above, that uses two key outputs from the sequential auction model: the average match quality and wage of each skill type of worker, which are both identified up to a scaling factor in the first stage of estimation. This scaling factor is the price of the intermediate good produced in a given skill sector, which is determined by the parameters of the KORV production function. The rest of this section describes each of these steps in greater detail, starting with estimation of the sequential auction model.

Sequential Auction Estimation: Job Contact Rates

The monthly job contact rate for employees, $\lambda_{1,i,t}$, is chosen so that the model matches the empirical proportion of individuals continuously employed in a year who have more than one employer (the multiple employer rate, denoted $\tau_{i,t}$). This moment is given in the model by equation (28).

$$\tau_{i,t} = 1 - \int_{\nu_{inf_{i,t}}}^{\nu_{max}} (1 - \lambda_{1,i,t}\bar{F}_{i,t}(\nu))^{12} dL_{i,t}(\nu) \tag{28}$$

In Appendix B, I show that this expression is independent of the match quality distribution meaning I can estimate job contact rates separately of distributional parameters. The expression is also an increasing monotonic function of $\lambda_{1.i}$ which implies this parameter is indeed identified when I estimate it by simulated method of moments, as set out in equation (29) (where $\hat{x}$ denotes the empirical counterpart of model moment x).

$$\lambda^*_{1,i,t} = \underset{\lambda_{1,i,t}}{\text{argmin}}\Big(\tau_t(\lambda_{1,i,t}) - \hat{\tau}_t\Big)^2 \tag{29}$$

Sequential Auction Estimation: Distribution of Match Heterogeneity

I assume that sampling distribution of match heterogeneity can be characterized by a lower truncated log normal distribution, and therefore can be fully described by three parameters: the mean and variance parameters, $\zeta^{\nu}_{i,t}$, $\eta^{\nu}_{i,t}$, and lower truncation point, $\nu_{inf_{i,t}}$. Note that by estimating the lower bounds directly I bypass the need to estimate job contact rates for the unemployed or replacement rates. This follows because my principal interest is to estimate the distribution of wages and match quality for workers in the intermediate goods market; unemployment conditions influence these variables through the lower bound of the match quality distribution only.

Given I have data on employees only, and not employers, a natural option to estimate $\zeta^{\nu}_{i,t}$ and $\eta^{\nu}_{i,t}$ is to use moments of the wage distribution for workers of each skill type $i \in u, s$. Note, however, that all wages of a given skill type are scaled by the price of the intermediate good, p_i (see equation (16)), which depends on the parameters of the KORV production function that I have yet to estimate. I therefore require the moment of the wage distribution that I will target to be scale invariant, and so choose the variance of log residual wages.

As both $\zeta^{\nu}_{i,t}$ and $\eta^{\nu}_{i,t}$ have a positive monotonic impact on match quality dispersion in the model, they will not be separately identified using the variance of log wages. I therefore set the value of $\zeta^{\nu}_{i,t}$ to target the mean of the sampling distribution, $\mathbb{E}^{F_{i,t}}(\nu)$, to an arbitrary fixed value (= 1). Note that this also avoids introducing a 'black-box' source of skills biased technological change via an increase in the relative means of the sampling distribution of match quality $\mathbb{E}^{F_{s,t}}(\nu)/\mathbb{E}^{F_{u,t}}(\nu)$ (Krusell et al. (2000) impose that the relative labor efficiency of skilled to unskilled workers is constant for the same reason). This does not rule out an endogenous increase in the mean of the cross section distribution of match quality $\mathbb{E}^{L_{i,t}}(\nu)$. The variance parameter of the sampling distribution of match quality, $\eta^{\nu}_{i,t}$, is left free to match the dispersion of residual log wages within a skill type i in the model to its empirical counterpart.

Finally I must estimate the lower bound of the distribution of match quality, $\nu_{inf_{i,t}}$. Provided the bargaining parameter is sufficiently high, a worker at a match of quality $\nu = \nu_{inf_{i,t}}$ will earn the lowest wage in the model's wage distribution, denoted $\underline{w}_{i,t}$, where $\underline{w}_{i,t} = \nu_{inf_{i,t}} \times p_{i,t}$.[21] Since all wages are scaled by the price of the intermediate good, $p_{i,t}$, which will not be estimated at this stage, rather than target the absolute lower bound of the wage distribution I target the ratio of the lower bound to the median wage: $\underline{w}_{i,t}(\nu_{inf_{i,t}})/Q^{50}_{w_{i,t}}(\zeta^{\nu}_{i,t}, \eta^{\nu}_{i,t}, \nu_{inf_{i,t}})$. When it comes to the empirical counterpart of this moment, I choose to use the average wages of workers in the bottom five percentiles of the wage distribution (again relative to the median) rather than the minimum of the empirical wage distribution as this is likely to be subject to significant measurement error.

In summary, I estimate the parameters of the sampling distribution, $\zeta^{\nu}_{i,t}, \eta^{\nu}_{i,t}$ and $\nu_{inf_{i,t}}$, by solving the minimization problem shown in equation (30), where $\hat{x}$ denotes the empirical counterpart of model moment x, and W is the weighting matrix.[22]

$$(\zeta^{\nu*}_{i,t}, \eta^{\nu*}_{i,t}, \nu^{*}_{inf_{i,t}}) = \underset{\zeta^{\nu}_{i,t}, \eta^{\nu}_{i,t}, \nu_{inf_{i,t}}}{\operatorname{argmin}} \; (m_t - \hat{m}_t)^T W (m_t - \hat{m}_t) \tag{30}$$

[21]In the model, the minimum wage in the population of workers will be paid to workers with match quality equal to the lower bound of the match distribution in the model when $\beta > \frac{\lambda_1}{\rho+\delta+two\lambda_1}$. This condition is derived from observing first that the wage expression in equation (16) is always decreasing in ν^-, so the lowest wage observable wage will certainly belong to those who have come from unemployment i.e. workers who have $\nu^- = \nu_{inf}$. Such workers will have a wage precisely equal to ν_{inf} when they are matched with the lowest match quality firms i.e. $\nu^+ = \nu^- = \nu_{inf}$. Finally a sufficient condition for this to be the lowest wage in the population is that the derivative of the wage expression with respect to the current match quality, ν^+, is positive for this worker and the second derivative is always positive. The latter condition always holds, and former holds when β is greater than the threshold shown above.

[22]The weighting matrix W, is chosen so I effectively minimize the percentage deviation of model moments from their empirical moments, which avoids the scale of absolute moment deviations biasing estimates i.e. $W = I.\frac{1}{\hat{m}}$.

$$m_t \equiv \big(var_{\log(w_{i,t})}(\zeta^{\nu}_{i,t}, \eta^{\nu}_{i,t}, \nu_{inf_{i,t}}), \underline{w}_{i,t}(\nu_{inf_{i,t}})/Q^{50}_{w_{i,t}}(\zeta^{\nu}_{i,t}, \eta^{\nu}_{i,t}, \nu_{inf_{i,t}}),$$
$$\mathbb{E}^{F_{i,t}}(\nu)(\zeta^{\nu}_{i,t}, \eta^{\nu}_{i,t}, \nu_{inf_{i,t}})\big)$$

I calculate the moments of the wage distribution in the model for a given guess of parameters by generating a sample of workers using the cross section distributions of workers' match quality and outside options given in equations (18) and (19) respectively, and then using equation (16) to derive the wages of these workers. Note that for notational convenience equation (30) suppresses the dependence of the model moments on job destruction rates, δ_i, and job contact rates, $\lambda_{1,i}$, which are taken from the data and estimated in the previous step respectively.

Sequential Auction Estimation: Other Parameters to be Calibrated

In the absence of matched employee and employer data, I set the bargaining parameter to $\beta = 0.95$. I find lower levels of the bargaining parameters mean the model struggles to simultaneously hit the level of the labor share and the rise in the graduate wage premium seen in the data. This occurs because the sequential auction part of the model sets an upper bound on the labor share in the overall model: incorporating a final goods sector with capital inputs will always lower the labor share relative to its level in the intermediate goods sector where labor is the only input. The upper bound on the labor share implied by the sequential auction results may be close to or even below the empirical labor share that I am targeting if the bargaining parameter is set too low. This issue is discussed in more detail in Appendix A. Although this calibrated bargaining parameter value appears high compared to some results in the micro literature, for example Cahuc et al. (2006), many of these estimates come from structural models that do not feature capital and so are not directly comparable to ours. Finally, I arbitrarily set the monthly discount rate to 0.004.

Adding Sequential Auction Results to KORV Estimation

I adopt essentially the same empirical approach as Krusell et al. (2000) i.e matching the models predictions for the evolution of the wage bill of skilled workers relative to that of unskilled workers and the labor share of income to their empirical counterparts and targeting a zero rate-of-return (RoR) difference between capital structure and capital equipment in the model. However, I make two key modifications to incorporate results from the sequential auction stage of my estimation approach.

The first modification is necessary because the unskilled and skilled labor inputs are not simply hours worked by the two types but rather the amount of intermediate goods from each skill type sector. The inputs U_t and S_t therefore become as defined in equation (9) where I multiply the labor inputs that KORV use (total hours in efficiency units) by the average match quality in each skill sector. Estimates of average match quality are derived from simulations using estimated parameters from the sequential auction part of my model, and are denoted $\mathbb{E}^{\hat{L}_{i,t}}(\nu) \equiv \int_{\nu_{\hat{inf}_{i,t}}}^{\nu_{max}} \nu \hat{\ell_{i,t}}(\nu)$ (where hats denote estimated variables or parameters).

Second average wages for a given skill type i are no longer simply the marginal product of that skill type in production of the final good, but are determined as specified in equation (22). I decompose this expression into two parts, as shown below.

$$\begin{aligned}
\mathbb{E}^{L_{i,t}}(w_{i,t}) \quad &= p_{i,t} \times \mathbb{E}^{L_{i,t}}(w_{i,t}, p_{i,t} = 1) \\
\mathbb{E}^{L_{i,t}}(w_{i,t}, p_{i,t} = 1) &\equiv \int_{\underline{\nu}}^{\nu_{max}} \Bigg[\nu - [1 + \kappa_{1,i}\bar{F}(\nu)]^2 \times \\
&\int_{\nu_{inf}}^{\nu} \frac{(1-\beta)[1 + \frac{\delta_i}{\delta_i+\rho}\kappa_{1,i}\bar{F}(x)]}{[1 + \frac{\delta_i}{\delta_i+\rho}\kappa_{1,i}\beta\bar{F}(x)][1 + \kappa_{1,i}\bar{F}(x)]^2} dx \Bigg] \ell_i(\nu) d\nu
\end{aligned} \tag{31}$$

Thus average wages are calculated by multiplying the price of the intermediate good $p_{i,t}$ (its marginal product in the production of the final good) by the average wages in the intermediate good sector when the price of the intermediate good is normalized to one $\mathbb{E}^{L_{i,t}}(w_{i,t}, p_{i,t} = 1)$. As with estimates for average match quality, I estimate $\mathbb{E}^{L_{i,t}}(w_{i,t}, p_{i,t} = 1)$ by using estimation results from the sequential auction part of my model.

To summaries, I adapt KORV's original methodology to include intermediate goods sectors with sequential auction labor markets via two modifications. First I scale the labor input of a given skill type i by a 'productivity scale' which is my estimate of the average match quality in their intermediate good sector, $\mathbb{E}^{\hat{L}_{i,t}}(\nu)$. Second, I then calculate average wages by multiplying the marginal product of a given intermediate good in the KORV production function (for a given parameter guess) by a 'wage scale' that is my estimate of average normalized wages in the relevant intermediate goods sector, $\mathbb{E}^{\hat{L}_{i,t}}(w_{i,t}, p_{i,t} = 1)$. Otherwise, estimation of the parameters of the KORV production function proceeds exactly as described in Section 4.1.

5. Results

This section starts by verifying that I can replicate the results provided in Krusell et al. (2000) when I use their estimation strategy and data. I also present the results of replicating KORV's methodology, i.e. with no frictions, for an updated

Table 1. Parameter Estimates: KORV vs Replication

Parameter	KORV findings	Replication Estimates
α	0.117	0.122
γ	-0.495	-0.45
σ	0.401	0.402
$\varepsilon_{S,K_{eq}}$ $(= 1/1-\gamma))$	0.669	0.689
$\varepsilon_{U,K_{eq}}$ $(= 1/1-\sigma))$	1.669	1.674
CSC Strength: $\varepsilon_{U,K_{eq}} - \varepsilon_{S,K_{eq}}$	1.001	0.984

Notes: Rows 2-4 show estimates of the subset of primitive parameters of the KORV production function that were published in Krusell et al. (2000). Row 5 shows the implied elasticity of substitution between capital equipment and skilled labor input, $\varepsilon_{S,K_{eq}}$. Row 6 shows the implied elasticity of substitution between capital equipment and unskilled labor input, $\varepsilon_{U,K_{eq}}$. Row 7 shows the implied strength of the capital skill complementarity (CSC) channel, as measured by $\varepsilon_{U,K_{eq}} - \varepsilon_{S,K_{eq}}$.

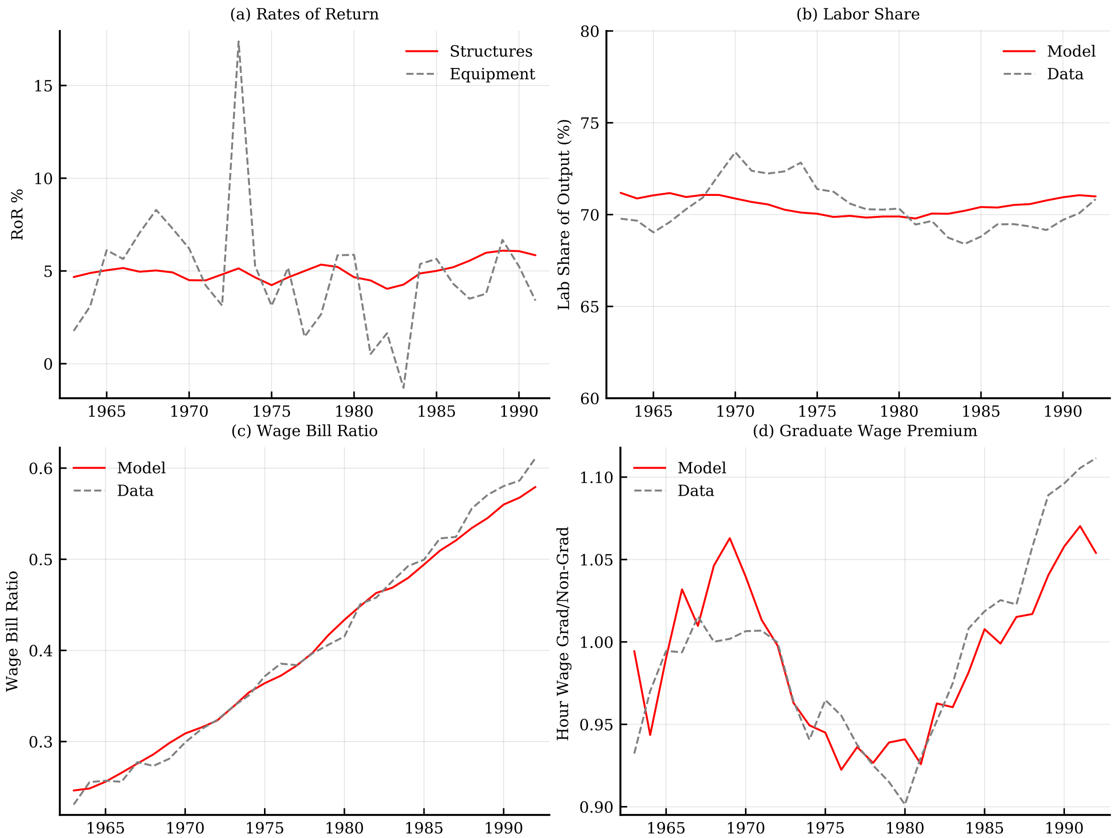
sample period. I then show results from estimation of the sequential auction model of the intermediate goods sectors, and finally I show the impact of incorporating intermediate goods sectors with search frictions into estimation of the KORV production function. When considering this impact my focus will be on how, if at all, estimates of capital skill complementarity change and how that changes explanations for the rise in the graduate wage premium.

5.1. **Replication of KORV methodology.** I am able to replicate results from KORV both in terms of fit to the author provided data (see Figure 7 for my fit to the data and Figure 8 for the equivalent figure in Krusell et al. (2000)) and in terms of parameter estimates (see Table 1). In particular, I estimate very similar levels of capital skill complementarity (as measured by the difference in the elasticity of substitution between unskilled labor and capital equipment, denoted $\varepsilon_{U,K_{eq}}$, and the elasticity of substitution between skilled labor and capital equipment, denoted $\varepsilon_{S,K_{eq}}$).

When I include more recent data in my replication of the KORV methodology, rather than using only their original sample period of 1963-1992, I find the model again fits the data well - see Figure 9.[23] Table 2 shows inclusion of more recent data decreases estimates of capital skill complementarity. A potential explanation for this is that the empirical growth in the graduate wage premium remains steady

[23] I have to switch from author provided data to publicly available data to extend the time period, which is why the parameter estimates for the original sample period shown in Table 2 differ from those in Table 1.

Figure 7. Replication of KORV



Notes: All model moments displayed in the figure are generated using estimated parameter values using my replication of KORV's methodology. Panel (a) of the figure compares the ex-post rates of return (RoR) on capital structures and equipment predicted by the model. Panels (b) through (d) compare model moments to their empirical counterparts for the labor share of income, the wage bill of skilled workers relative to that of unskilled workers, and the graduate wage premium respectively.

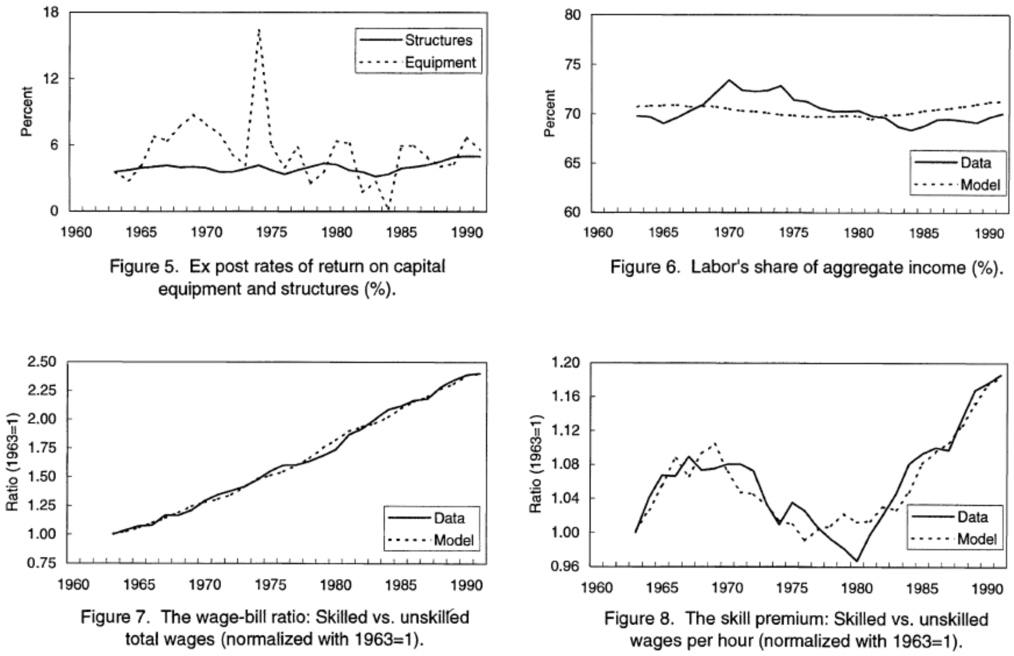
after 1992 despite an sharp acceleration in capital equipment growth (see Figure 1); to reconcile these two patterns the model requires a lower estimate of capital skill complementarity than in the original sample period.

5.2. **Sequential Auction Results.**

Sequential Auction Results: Job Contact Rates

The first row of Figure 10 shows my estimates of job contact rates for unskilled and skilled workers, in absolute and relative terms (I plot a six year rolling average

FIGURE 8. KORV's original fit

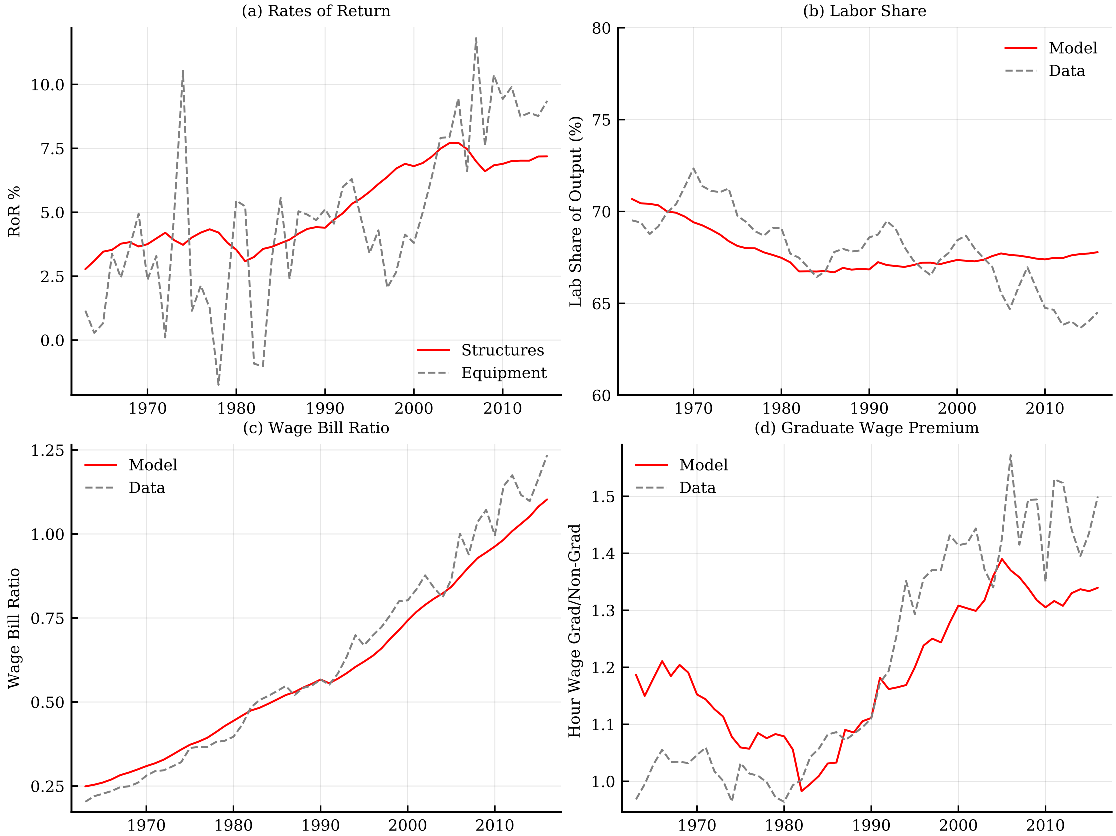


Notes: I am unable to directly provide model predictions using KORV's parameter estimates, as the author's only provide a subset of the relevant estimates, so I directly reproduce the figure from Krusell et al. (2000) showing the fit of their model to the data.

of estimated relative contact rates to emphasize the time trend). The second row of the same figure shows the empirical targets these estimates are based on - the multiple employer rate - and the corresponding model moments.

I am able to exactly match the model moments to their empirical counterparts. Estimated job contact rates do not exactly track the data on multiple employer rates because job contact rates are not the sole determinant of the multiple employer rate: job destruction also plays a role, as shown in equation (28). The intuition here is that workers who exit the labor market more frequently will spend more time at the bottom of the job ladder and hence move employers more often due to favorable job offers. This explains why skilled workers are estimated to have significantly higher job contact rates than unskilled workers despite similar multiple employer rates: the higher job contact rate for skilled workers offsets their lower job destruction rates to leave the multiple employer rate at a similar level to unskilled workers. So while casual inspection of multiple employer rates alone might suggest similar levels of employer competition for skilled and unskilled workers, the findings here illustrate that interpreting the data through a structural model

FIGURE 9. Replication of KORV: Extended Sample Period



Notes: All model moments displayed in the figure are generated from estimated parameter values using my replication of KORV's methodology and updating sample data to the latest available. Panel (a) of the figure compares the ex-post rates of return (RoR) on capital structures and equipment predicted by the model. Panels (b) through (d) compare model moments to their empirical counterparts for the labor share of income, the wage bill of skilled workers relative to that of unskilled workers, and the graduate wage premium respectively.

leads to a quite different conclusion i.e. that skilled workers enjoy much higher job contact rates than unskilled workers.

However, the time trend is for estimated job contact rates for skilled workers to increase relative to those of unskilled workers until the late 1990s and then decrease thereafter.

Sequential Auction Results: Distribution of Match Quality

For each of my two skill types, I estimate three parameters of the match quality distribution, which is assumed to take a truncated log normal form: the mean,

Table 2. Parameter Values with Extended Sample Period

Parameter	Original Sample Period	Extended Sample Period
λ	0.557	0.529
μ	0.489	0.345
α	0.111	0.123
γ	-0.463	-0.266
σ	0.453	0.427
$\varepsilon_{S,K_{eq}}$ $(= 1/1-\gamma))$	0.684	0.79
$\varepsilon_{U,K_{eq}}$ $(= 1/1-\sigma))$	1.829	1.746
CSC Strength: $\varepsilon_{U,K_{eq}} - \varepsilon_{S,K_{eq}}$	1.145	0.956

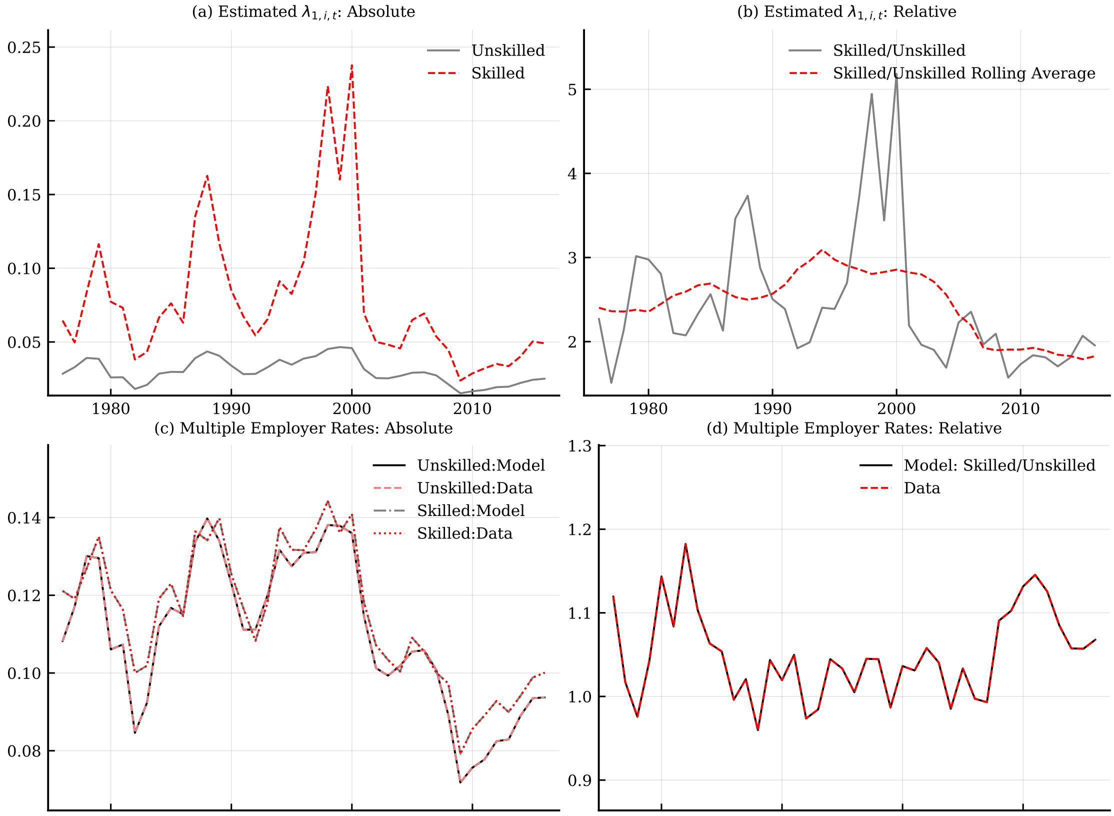
Notes: Rows 2-6 show estimates of the primitive parameters of the KORV production function. Row 7 shows the implied elasticity of substitution between capital equipment and skilled labor input, $\varepsilon_{S,K_{eq}}$. Row 8 shows the implied elasticity of substitution between capital equipment and unskilled labor input, $\varepsilon_{U,K_{eq}}$. Row 9 shows the implied strength of the capital skill complementarity (CSC) channel, as measured by $\varepsilon_{U,K_{eq}} - \varepsilon_{S,K_{eq}}$.

variance and lower bound parameters, $\zeta^{\nu}_{i,t}, \eta^{\nu}_{i,t}$ and $\nu_{inf_{i,t}}$ respectively. I am able to match the model to the targeted empirical moments precisely in the case of both $\eta^{\nu}_{i,t}$ and $\nu_{inf_{i,t}}$ where the relevant targets are log residual wage variance and the ratio of average wages of workers in the bottom five percentiles of the wage distribution to median wages respectively. Figures 11 and 12 show parameter estimates for $\eta^{\nu}_{i,t}$ and $\nu_{inf_{i,t}}$ respectively, and illustrate the close fit of the model moments to the data. Estimates of $\zeta^{\nu}_{i,t}$ are in a sense less relevant since they are simply set at the level necessary to keep the mean of the sampling distribution of match quality constant at an arbitrary target ($\mathbb{E}^{F_{i,t}}(\nu) = 1$).

The estimated variance parameter of the sampling distribution of match quality, $\hat{\eta}^{\nu}_{i,t}$, for skilled workers increases over time relative to the equivalent parameter for unskilled workers, mirroring changes in the empirical target (residual log wage variance). Estimates of the lower bound of the match quality distribution, $\hat{\nu}_{inf_{i,t}}$ decrease in relative terms for skilled workers, again mirroring the trend in the empirical target.

5.3. **Impact of Sequential Auction Estimates on KORV results.** As argued in Section 4.2, the results of my estimation of the sequential auction structure of the intermediate goods market can be fully summarized by two series for the purposes of estimating the parameters of the KORV production function. The first series is the 'productivity scale', which is the estimate of the average match quality by skill $\mathbb{E}^{L_{i,t}}(\nu)$ that I use to scale labor inputs. The second series is the'wage scale', $\mathbb{E}^{L_{i,t}}(w_{i,t}, p_{i,t} = 1)$, which relates to average wages of skill type i via the

Figure 10. Job Mobility

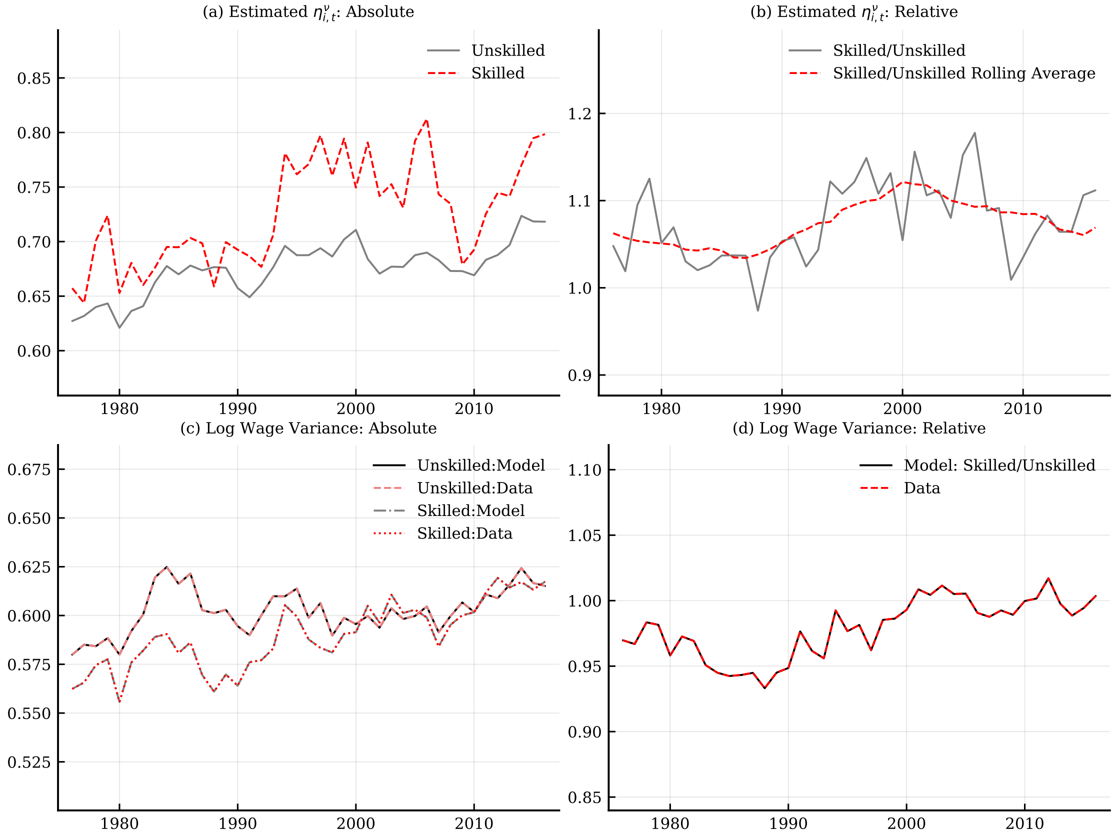


Notes: The first row of the figure shows estimated job contact rates for employees, $\lambda_{1,i,t}$, in absolute terms for unskilled workers and skilled workers - Panel (a) - and for skilled workers relative to unskilled workers - Panel (b). The second row shows implied model predictions for the multiple employer rate, and their empirical counterparts, shown in absolute and relative terms in Panels (c) and (d) respectively.

identity $\mathbb{E}^{L_{i,t}}(w_{i,t}) = p_{i,t}\mathbb{E}^{L_{i,t}}(w_{i,t}, p_{i,t} = 1)$. These series are plotted in absolute and relative terms in Figure 13, with a rolling 6 year average of the relative series added to emphasize the relevant trends.

Figure 13 shows that the presence of search frictions can explain a positive skill premium since the relative wage scale is estimated to be consistently above one. Reflecting trends in estimated job contact rates, the relative productivity and wage scaling factors of the high skill workers are increasing, albeit very mildly, until around the mid to late 1990s, but then decrease after this. However, this trend is not strong enough to significantly change estimates of the parameters in the KORV production function as shown in Table 3. In particular, the estimate of capital skill complementarity (the difference between the elasticity of substitution between

FIGURE 11. Match Quality Dispersion

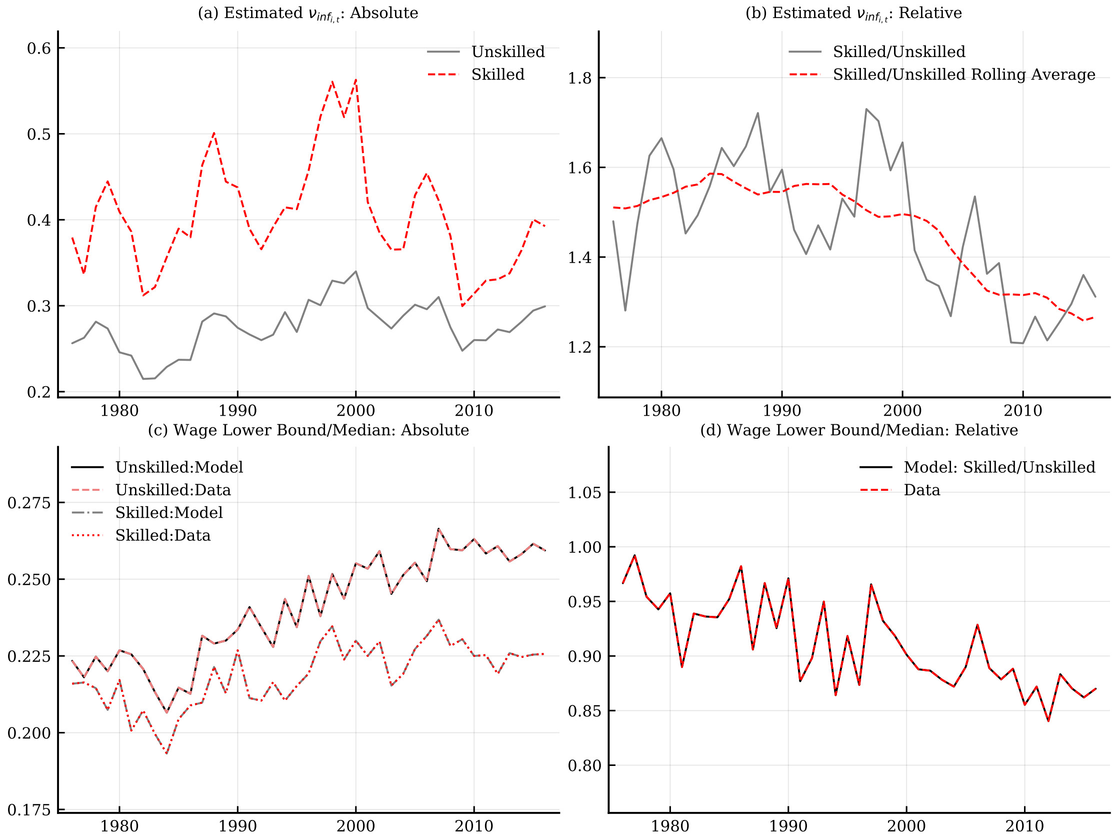


Notes: The first row of the figure shows estimates of the variance parameter of the match quality distribution, $\eta^{\nu}_{i,t}$, in absolute terms for unskilled workers and skilled workers - Panel (a) - and for skilled workers relative to unskilled workers - Panel (b). The second row shows implied model predictions for the variance of log wages and their empirical counterparts (where the empirical variance is given for residual log wages, after controlling for education, race, sex and year). This moment is shown in absolute and relative terms in Panels (c) and (d) respectively.

unskilled labor and capital equipment and skilled labor and capital equipment, $\varepsilon_{U,K_{eq}} - \varepsilon_{S,K_{eq}}$ is very similar. The model with frictions seems to fit the data slightly less accurately than the original KORV formulation as shown in Figure 14.

The model with frictions is still entirely reliant on the capital skill complementarity (CSC) channel to generate an increase in the graduate wage premium, as can be seen by examining model predictions when I shut down the CSC channel by imposing $\hat{\sigma} = \hat{\gamma}$: Figure 15 shows that both the model with frictions and without in fact predict large falls in the graduate wage premium, due to the increase in

FIGURE 12. Match Quality Lower Bound



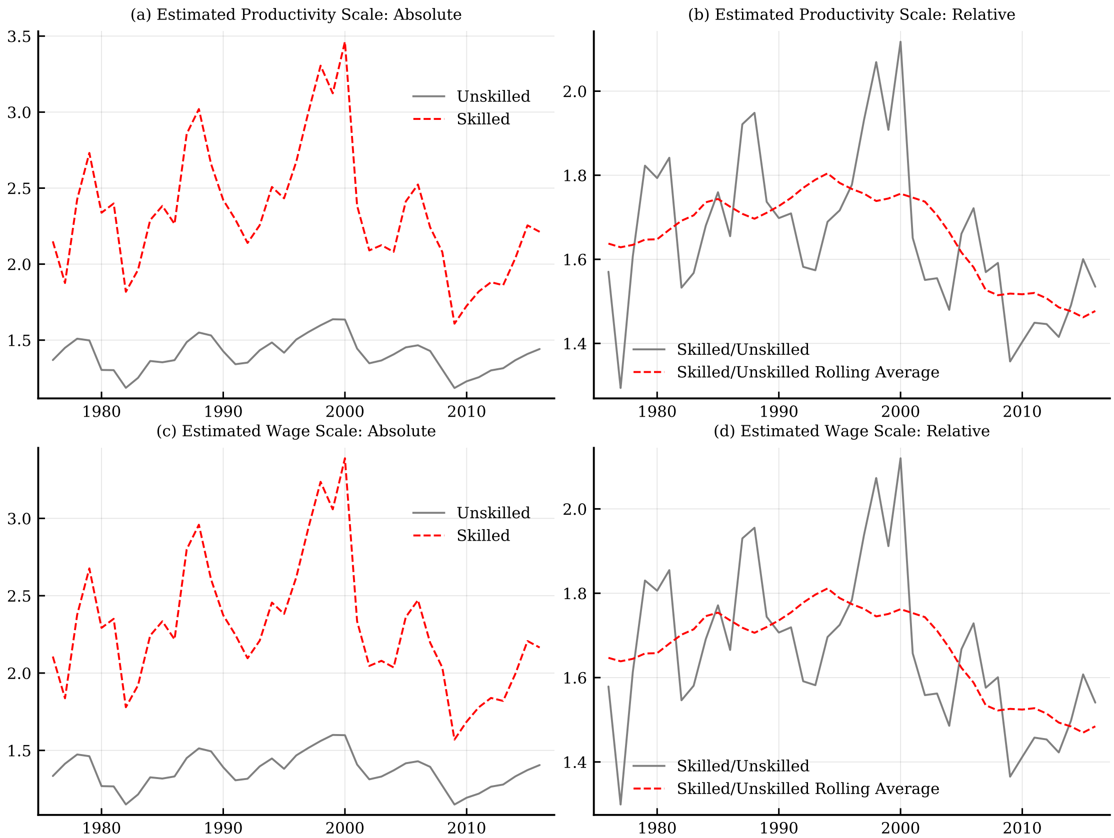
Notes: The first row of the figure shows estimates of the lower bound of the match quality distribution, $\nu_{inf,i,t}$, in absolute terms for unskilled workers and skilled workers - Panel (a) - and for skilled workers relative to unskilled workers - Panel (b). The second row shows implied model predictions for the lower bound of the wage distribution as ratio of the median wage, and their empirical counterparts, shown in absolute and relative terms in Panels (c) and (d) respectively.

the relative supply of graduates, when there is no CSC. This illustrates that the CSC channel is responsible both for offsetting the negative impact of the rise in the relative supply of skilled workers on the predicted graduate wage premium, and for matching the increase in the wage premium seen in the data.

6. Conclusion

This paper develops an empirically testable model that combines the production framework specified in Krusell et al. (2000) with the sequential auction model of Cahuc et al. (2006). This model has the potential to identify the contribution of changes to institutions, search frictions and firm heterogeneity to growing wage

FIGURE 13. Scale Factors



Notes: The first row of the figure shows estimates of the mean of the match quality distribution, $\mathbb{E}^{L_{i,t}}(\nu)$ (the 'productivity scale'), in absolute terms for unskilled workers and skilled workers - Panel (a) - and for skilled workers relative to unskilled workers - Panel (b). The second row of the figure shows estimates of the mean wage of workers when the price of the intermediate good they produce is normalized to one, $\mathbb{E}^{L_{i,t}}(w_{i,t}, p_{i,t} = 1)$ (the 'wage scale'), in absolute terms for unskilled workers and skilled workers - Panel (c) - and for skilled workers relative to unskilled workers - Panel (d).

inequality alongside more traditional explanations such as technological change and changes to the relative supply of skill groups. The model provides a theoretical grounding for findings from the empirical literature e.g. on the importance of firm heterogeneity and institutions for growing wage inequality (Card et al. (2013), Song et al. (2015) and Lee (1999)).

The empirical contribution of this paper is to examine whether adding a sequential auction labor market structure to Krusell et al. (2000) materially changes estimates of capital-skill complementarity. If I maintain consistency with Krusell et al. (2000) by using CPS labor market data only i.e. where no employer side information is

Table 3. KORV parameter values: the importance of frictions

Parameter	With Frictions	Without Frictions
λ	0.462	0.521
μ	0.462	0.442
α	0.118	0.127
γ	-0.187	-0.202
σ	0.316	0.347
$\varepsilon_{S,K_{eq}}$ $(= 1/1 - \gamma))$	0.843	0.832
$\varepsilon_{U,K_{eq}}$ $(= 1/1 - \sigma))$	1.462	1.531
CSC Strength: $\varepsilon_{U,K_{eq}} - \varepsilon_{S,K_{eq}}$	0.619	0.699

Notes: Rows 2-6 show estimates of the primitive parameters of the KORV production function. Row 7 shows the implied elasticity of substitution between capital equipment and skilled labor input, $\varepsilon_{S,K_{eq}}$. Row 8 shows the implied elasticity of substitution between capital equipment and unskilled labor input, $\varepsilon_{U,K_{eq}}$. Row 9 shows the implied strength of the capital skill complementarity (CSC) channel, as measured by $\varepsilon_{U,K_{eq}} - \varepsilon_{S,K_{eq}}$.

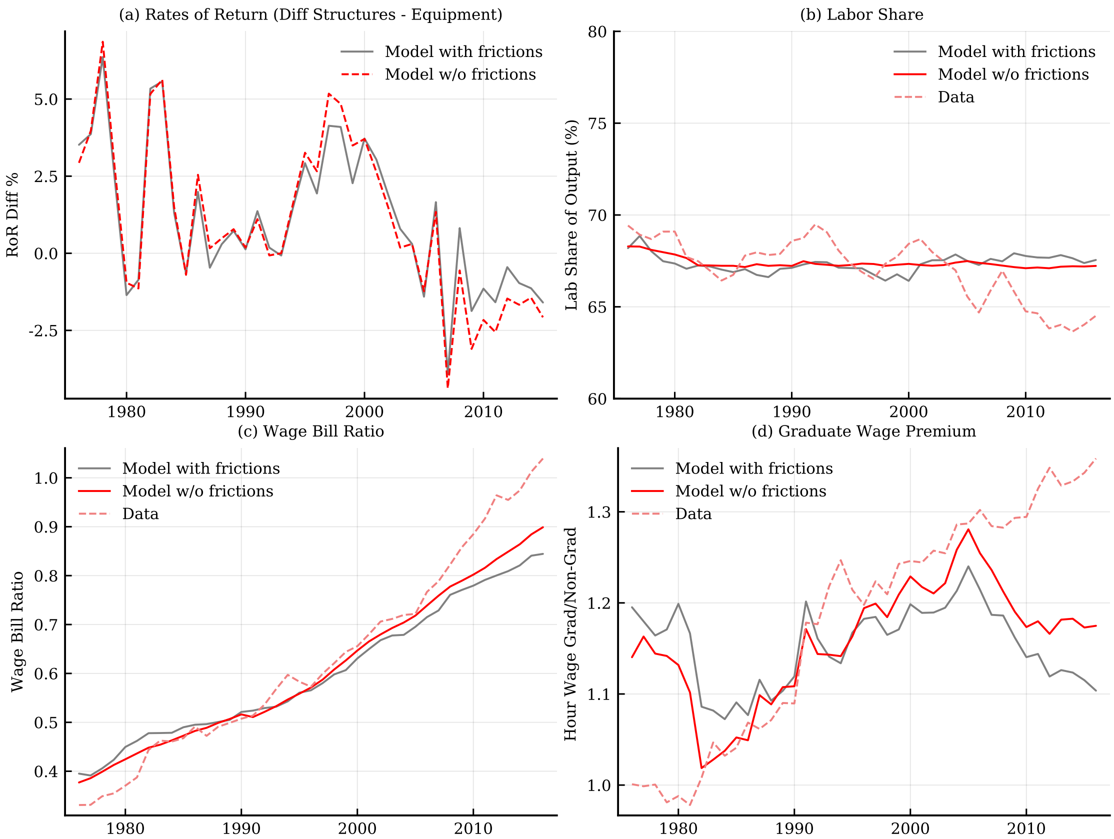
used, I find that estimates of capital-skill complementarity are not significantly changed by allowing for labor market frictions.

This reflects the fact that the empirical measures of job market frictions I use, while favoring skilled workers in levels terms, do not move decisively in favor of either skilled or unskilled workers over the sample period. Job destruction rates move in favor of unskilled workers relative to skilled workers, however, this is partly offset by an increase in estimated match quality dispersion for skilled workers which means climbing the job ladder brings greater rewards and boosts their average pay. Estimated job contact rates for skilled workers relative to those of unskilled workers increase gradually until the late 1990s and decrease thereafter.

To maintain consistency and comparability with Krusell et al. (2000) I do not use any direct data on firm heterogeneity, which limits my ability to identify changes to the distribution of match heterogeneity and prevents identification of bargaining parameters, which could be one way to capture changes to the institutional environment. Adapting this framework to matched employer employee data is therefore a promising line of future research.

I also make the simplifying assumption that job contact rates are exogenous in my model, in keeping with Cahuc et al. (2006). However, this means changes in the use of capital, and hence the relative demand for skilled labor, have no impact on the job market frictions these workers face. Adding endogenous vacancy creation to the model, while representing a significant theoretical and empirical challenge,

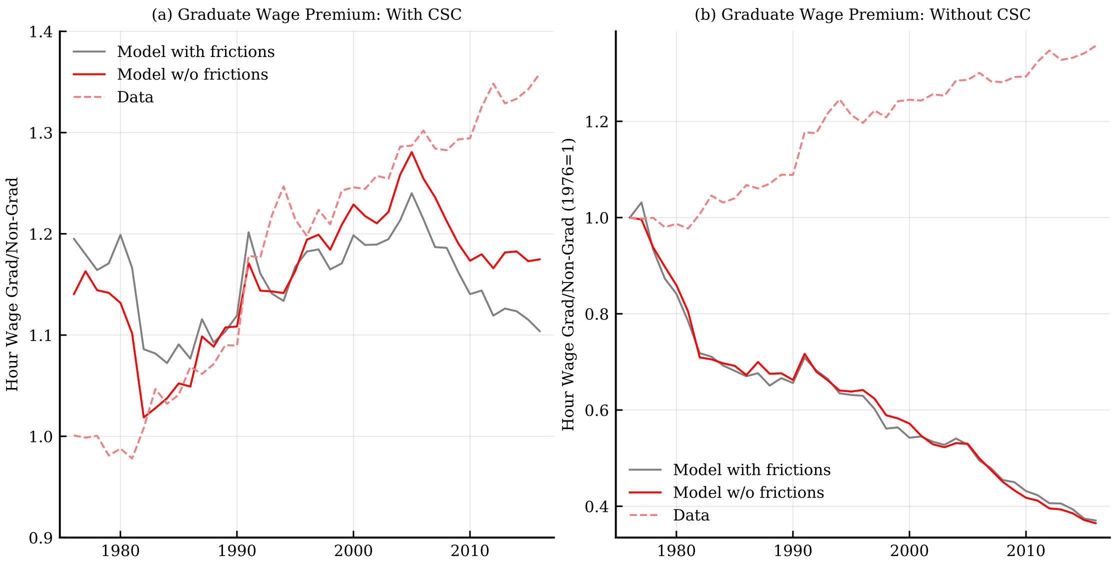
FIGURE 14. Model Fit: With and Without Frictions



Notes: The model moments displayed in the figure are generated both from estimated parameter values using my replication of KORV's methodology i.e without frictions (the 'w/o frictions' series) and using estimates when incorporating frictions (the 'with frictions' series). Panel (a) of the figure compares the difference in ex-post rates of return (RoR) between capital structures and equipment predicted by the two versions of the model. Panels (b) through (d) compare model moments to their empirical counterparts for the labor share of income, the wage bill of skilled workers relative to that of unskilled workers, and the graduate wage premium respectively.

would shed light on the links and feedback mechanisms between wage inequality, technology and labor market frictions.

Figure 15. Model Fit: No Capital Skill Complementarity (CSC)



Notes: The model moments displayed in the figure are generated both from estimated parameter values using my replication of KORV's methodology i.e without frictions (the 'w/o frictions' series) and using estimates when incorporating frictions (the 'with frictions' series). Panel (a) of the figure shows model predictions for the graduate wage premium with all parameters at their baseline estimated values. Panel (b) of the figure shows model predictions for the graduate wage premium when I shut down the capital skill complementarity (CSC) channel both for the model with and without frictions, by setting $\hat{\sigma} = \hat{\gamma}$.

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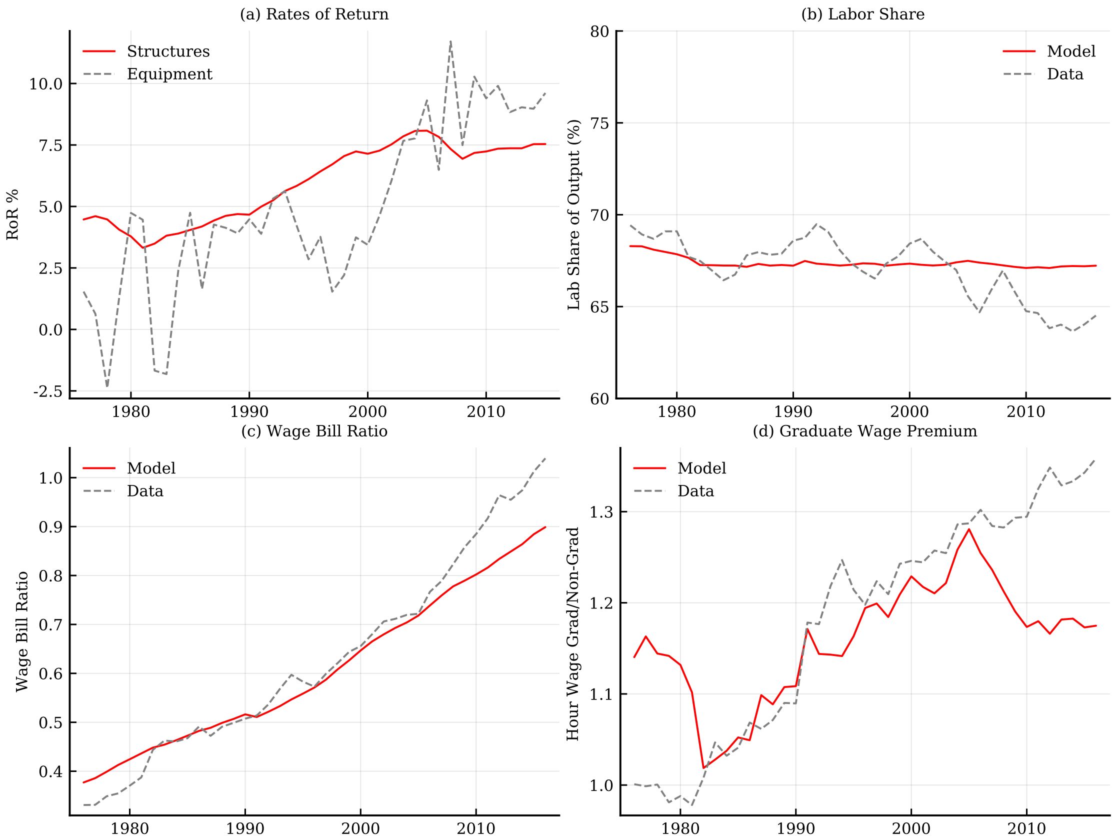
Appendix A. Model Results and Bargaining Power

This Appendix discusses the sensitivity of my results to the choice of the bargaining parameter. In my baseline estimation I impose a high level of bargaining power for both worker types ($\beta_u = \beta_s = 0.95$). I find that when I set the bargaining parameter at significantly lower levels, i.e. 0.75 or 0.5, and estimate the parameters of the KORV production function there is an acute tension between the model's ability to match both the rise in the graduate wage premium and the level of the labor share of output. The rest of this Appendix explains this tension and its quantitative impact. Overall I find that only a relatively high bargaining parameter allows the model to match the relevant trends in the data.

I first consider the intuition for why there might be a tension between matching the rise in the graduate wage premium and level of the labor share at lower levels of the bargaining parameter. First recall that the original, competitive, version of the KORV model is relatively successful at matching both the rise in the graduate wage premium and the labor share: see Figure 16. When I introduce the sequential auction model into this set-up, average wages will now be lower than the marginal product of labor if the bargaining parameter is significantly less than unity and for realistic job contact rates. In other words, the labor share will be lower in the model with frictions than in the original KORV environment for a given set of production function parameters. When I estimate the KORV parameters in my frictional labor market model, and have a low level of bargaining power, the estimation approach compensates for the downwards pressure this puts on the labor share by making labor more important (and capital less important) in the production of output. However, this jeopardizes the ability of the model to match

FIGURE 16. KORV with perfect competition



Notes: The model moments displayed in the figure are generated using estimated parameter values when I replicate KORV's methodology i.e. with perfect competition and no search frictions. Panel (a) of the figure shows predicted ex-post rates of return (RoR) on capital structures and equipment. Panels (b) through (d) compare model moments to their empirical counterparts for the labor share of income, the wage bill of skilled workers relative to that of unskilled workers, and the graduate wage premium respectively.

the graduate wage premium since the increased use of capital equipment is the main channel that pushes the wage premium up.

To illustrate this quantitative impact of this tension, consider estimates of the KORV production function parameters when I set the bargaining parameter to 0.5 for both unskilled and skilled workers - see Table 4 and Figure 17 for the corresponding model predictions. The estimate of α, the exponent of capital structures (K_{st}), hits the zero lower bound, and it also delivers lower levels of λ, the coefficient of capital equipment since this too increases the labor share. However a lower level of λ limits the channel of capital skill complementarity - see equation (8) - and means that although the model can fit the labor share to a reasonable approximation, it completely misses the rise in the graduate wage premium: see Figure 17. Indeed the fit is much worse than that of the

Table 4. KORV parameter values: bargaining parameter impact

Parameter	No Frictions (KORV)	Baseline ($\beta = 0.95$)	$\beta = 0.5$
λ	0.521	0.462	0.219
μ	0.442	0.462	0.742
α	0.127	0.118	0.0
γ	-0.202	-0.187	-0.277
σ	0.347	0.316	0.187
$\varepsilon_{S,K_{eq}}$ $(= 1/1 - \gamma))$	0.832	0.843	0.783
$\varepsilon_{U,K_{eq}}$ $(= 1/1 - \sigma))$	1.531	1.462	1.23
CSC Strength: $\varepsilon_{U,K_{eq}} - \varepsilon_{S,K_{eq}}$	0.699	0.619	0.447

Notes: Rows 2-6 show estimates of the primitive parameters of the KORV production function. Row 7 shows the implied elasticity of substitution between capital equipment and skilled labor input, $\varepsilon_{S,K_{eq}}$. Row 8 shows the implied elasticity of substitution between capital equipment and unskilled labor input, $\varepsilon_{U,K_{eq}}$. Row 9 shows the implied strength of the capital skill complementarity (CSC) channel, as measured by $\varepsilon_{U,K_{eq}} - \varepsilon_{S,K_{eq}}$.

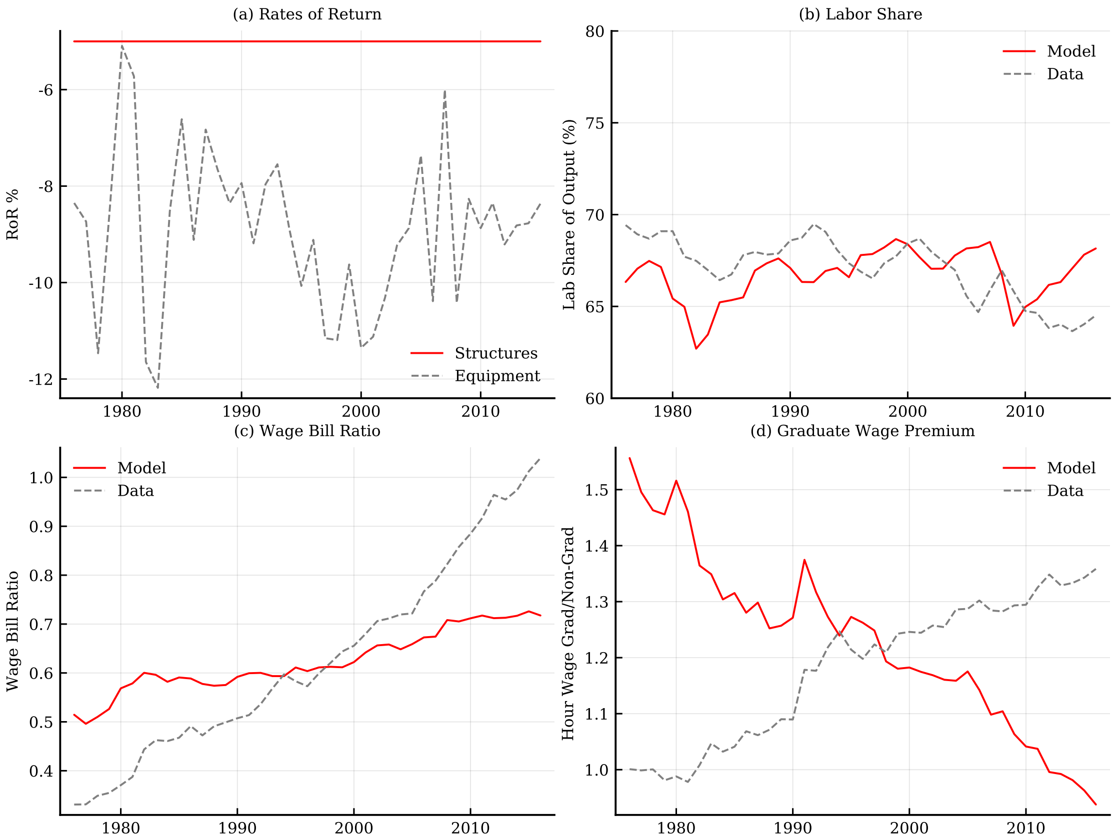
purely competitive set-up in KORV: see Figure 16. Increasing the bargaining parameter from 0.5 to 0.95 improves the results significantly - see Figure 18. While much of the micro evidence points to much lower levels of the bargaining parameter, generally such estimates are highly model dependent.

Appendix B. Identification

There are two sets of parameters to identify in my model: the parameters of the KORV production function, and those in the sequential auction model of the labor markets in the intermediate goods sectors. While Krusell et al. (2000) do not explicitly discuss identification in their paper, they do refer to the results of a companion empirical paper Ohanian et al. (1997) which shows their estimation strategy is successful at identifying the true parameters in Monte Carlo simulations. As my estimation of the parameters of the KORV production function very closely follows their method, and is done separately and subsequently to estimation of the sequential auction parameters, I do not repeat that exercise here and instead rely on their identification results.

The sequential auction structure of the labor market in my model is no different from Cahuc et al. (2006), however I use employee reported data (from the CPS) to estimate the relevant parameters, whereas Cahuc et al. (2006) used matched-employee-employer (MEE) data. I chose to use CPS data because a key motivation for this paper is to test the robustness of findings in Krusell et al. (2000) to incorporating frictions; I therefore sought to maintain as much consistency as possible to their estimation approach which used CPS data for wages and labor input. However, the MEE data that Cahuc et al. (2006) use plays a key role in their identification strategy so it is worth considering

FIGURE 17. KORV with frictions: $\beta = 0.5$



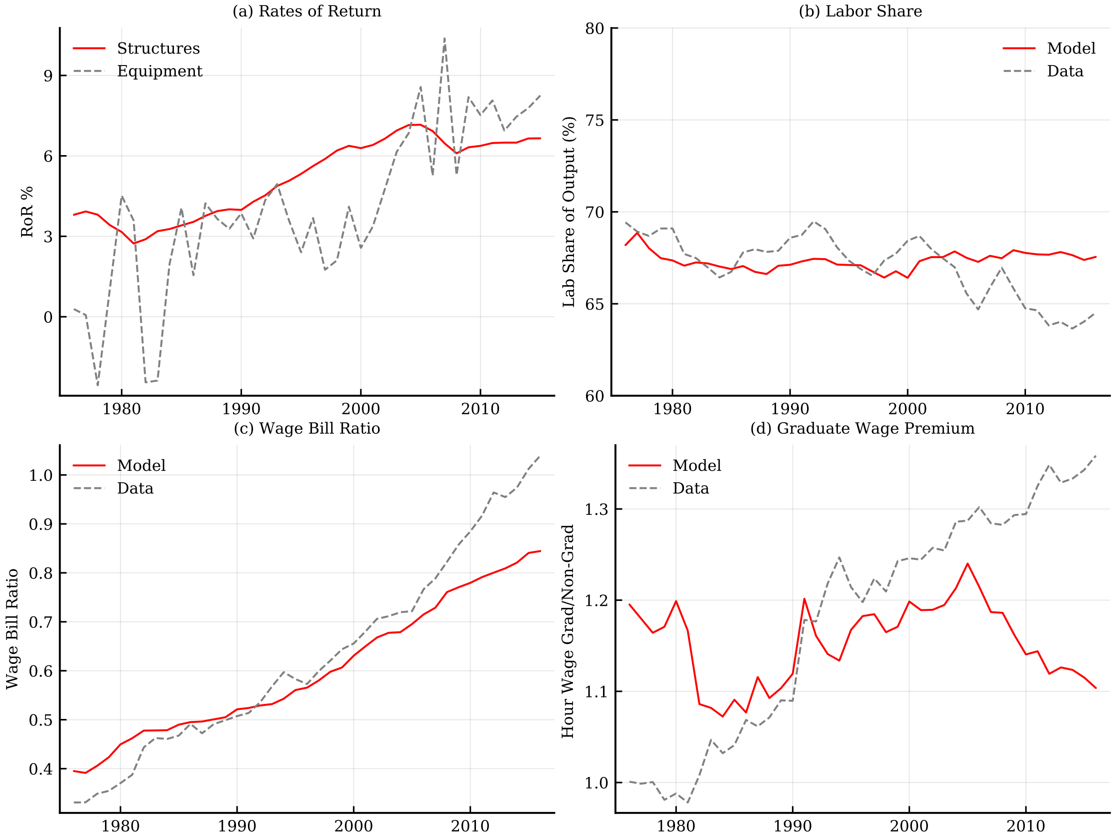
Notes: The model moments displayed in the figure are generated using estimated parameter values when I incorporate frictions but now with the bargaining parameter set uniformly at 0.5 (rather than 0.95). Panel (a) of the figure shows predicted ex-post rates of return (RoR) on capital structures and equipment. Panels (b) through (d) compare model moments to their empirical counterparts for the labor share of income, the wage bill of skilled workers relative to that of unskilled workers, and the graduate wage premium respectively.

whether the parameters I wish to identify in the sequential auction model are identified when using employee data only.

First bargaining parameters by worker skill level are much more difficult, if not impossible, to identify without some form of employer information. In the absence of such data, neither match output nor firm fixed effects are observable or estimable and hence reliable estimates of bargaining parameters are not readily available. This is why I choose to set bargaining parameters by assumption.[24] The remaining objects of interest in the sequential auction model are job contact rates, (note job destruction rates come straight

[24]The analysis of Appendix A suggests the labor share of income is informative about the average bargaining power of all workers, however it would not help to estimate bargaining parameters by skill level.

Figure 18. KORV with frictions - baseline bargaining power: $\beta = 0.95$



Notes: The model moments displayed in the figure are generated using estimated parameter values when I incorporate frictions and set the bargaining parameter at its baseline value of 0.95. Panel (a) of the figure shows predicted ex-post rates of return (RoR) on capital structures and equipment. Panels (b) through (d) compare model moments to their empirical counterparts for the labor share of income, the wage bill of skilled workers relative to that of unskilled workers, and the graduate wage premium respectively.

from the data) and the distribution of match quality, where I will consider the possibility of both non-parametric and parametric identification.

B.1. **Job Contact Rates.** There are two job contact rates in the sequential auction model for each skill type of worker: those for the unemployed and employed: $\lambda_{0,i}$ and $\lambda_{1,i}$ respectively. $\lambda_{0,i}$ determines the unemployment rate and, because it influences the outside option of workers, the minimum match quality of firm that a worker will accept an offer at. However, the unemployment rate does not play a role in the estimation of the KORV parameters (since labor input is total hours worked by workers and is taken straight from the data) or in the estimation of any other parameters in the sequential auction model, and I will estimate the lower bound of acceptable match quality directly, as described in the next section. I therefore have no need to estimate $\lambda_{0,i}$.

I instead focus on estimation of $\lambda_{1,i}$, which is key for determining both average match quality, and average wages of worker of a given skill type. Both variables play a role in estimating the parameters of the KORV production function, as described in Section 5.3.

I estimate $\lambda_{1,i}$ using SMM and targeting the proportion of continuous employed workers in a given year who have moved employers at least once (the multiple employer rate). I denote this proportion τ_i. In the model, the expression for this moment is given in equation 32, which is obtained by substituting the expression for the cross section distribution of match quality in equation (20) into equation (28).

$$\tau_i = 1 - \int_{\nu_{inf_i}}^{\nu_{max}} (1 - \lambda_{1,i,}\bar{F}_i(\nu))^{12} \frac{1 + \kappa_{1,i}}{[1 + \kappa_{1,i}\bar{F}_i(\nu)]^2} f_i(\nu) d\nu \tag{32}$$

As I am estimating $\lambda_{1,i}$ separately, and prior to, the estimation of the match quality distribution F, I require that equation (32) is independent of F. This can be proven by integrating by change of variable i.e. if I let $r = \bar{F}_i(\nu)$ so that $\frac{dr}{d\nu} = -f(\nu)$ the expression for τ becomes as shown in equation (33), which is independent of F.

$$\tau_i = 1 - \int_0^1 (1 - \lambda_{1,i,t} r)^{12} \frac{1 + \kappa_{1,i}}{[1 + \kappa_{1,i} r]^2} dr \tag{33}$$

The presence of the twelfth order polynomial in equation (33) hinders an analytical proof of identification, however it is easy to verify with a symbolic equation solver that this expression is a positive monotonic function of $\lambda_{1,i}$ which given the quadratic objective function in SMM proves identification of $\lambda_{1,i}$. This result is not surprising given it is possible to prove (analytically) that the monthly steady state job mobility rate is increasing in $\lambda_{1,i}$.

B.2. **Distribution of Match Quality.** There are two key considerations in the identification of the distribution of match quality. The first consideration is whether the distribution can be non-parametrically identified or not. I will argue that it can be, but only by relying heavily on the structure of the model. Therefore when it comes to estimation I prefer to assume a log normal distribution of match quality. The second consideration is then whether the parameters of this distribution are identified. I will estimate the parameters of the match quality distribution by targeting moments of the empirical wage distribution. However, higher order moments of the wage distribution in the model are not tractable, hindering an analytical proof of identification. I instead present evidence from Monte Carlo simulations that my estimation strategy can identify the 'true' parameters of the match quality distribution.

I start by showing that, in theory, the match distribution could be identified non-parametrically. A worker's wage depends both on their current employer's match quality ν^+ and their outside option match quality (the second highest quality match they've had contact with, denoted ν^-) as shown in equation (34). I therefore can't simply invert the wage equation to back out the quality of the current match, ν^+. Note I assume that the other parameter values in the equation are known due to the identification arguments presented above for job contact rates, and because other parameters either come straight from the data, like job destruction rates, or are set by assumption, like the bargaining parameter and discount factor.

$$\phi(p_i, \nu^-, \nu^+) = p_i\left(\nu^+ - (1-\beta)\int_{\nu^-}^{\nu^+} \frac{\rho + \delta + \lambda_1 \bar{F}(x)}{\rho + \delta + \lambda_1 \beta \bar{F}(x)} dx\right) \tag{34}$$

While the general wage equation for workers is not immediately helpful for identification, workers who were unemployed in the previous period and then get a job ('entrant workers') have a common level of ν^-, which equals ν_{inf_i}, the lower bound of the match quality distribution. Entrants will therefore be paid the wage shown in equation (35).

$$\phi(p_i, \nu_{inf_i}, \nu^+) = p_i\left(\nu^+ - (1-\beta)\int_{\nu_{inf_i}}^{\nu^+} \frac{\rho + \delta + \lambda_1 \bar{F}(x)}{\rho + \delta + \lambda_1 \beta \bar{F}(x)} dx\right) \tag{35}$$

I argued previously that if the bargaining parameter is high enough to guarantee that wages are an increasing function of the employer's match quality (which is the case in my baseline), then ν_{inf} is identified as the lower bound of wages in the empirical wage distribution. Therefore, in principle, I could identify the distribution of ν by inverting equation (12) for each wage in the empirical distribution of entrants' wages. This inversion can be done as follows: I start by letting $w = \phi(p_i, \nu_{inf_i}, \nu^+)$ and differentiating w with respect to ν^+ to get:

$$\begin{aligned}
\frac{dw}{d\nu+} &= p_i\left[1 - (1-\beta)\frac{\rho + \delta_i + \lambda_{1,i}\bar{F}_i(\nu^+)}{\rho + \delta_i + \lambda_{1,i}\beta\bar{F}_i(\nu^+)}\right] \\
&= p_i\left[\frac{\beta(\rho + \delta_i) + (2\beta - 1)\lambda_{1,i}\bar{F}_i(\nu^+)}{\rho + \delta_i + \lambda_{1,i}\beta\bar{F}_i(\nu^+)}\right] \\
\implies \frac{d\nu+}{dw} &= \frac{1}{p_i}\frac{\rho + \delta_i + \lambda_{1,i}\beta\bar{F}_i(\nu^+)}{\beta(\rho + \delta_i) + (2\beta - 1)\lambda_{1,i}\bar{F}_i(\nu^+)} \qquad (36)
\end{aligned}$$

Further note that under the assumption I have made about the bargaining parameter, a worker's wage is an increasing function of the match quality of their employer (ν^+), which implies that $\bar{F}_i(\nu^+) = \bar{F}_i^w(w(\nu^+))$. This is helpful since, while $\bar{F}_i(\nu^+)$ is not observable in the data, $\bar{F}_i^w(w(\nu^+))$ is. Substituting $\bar{F}_i(\nu^+) = \bar{F}_i^w(w(\nu^+))$ into equation (36) I can then derive an expression for $\nu+$ in terms of w by solving this differential equation.

However, this relies heavily on the structure of the model and, moreover, on part of the structure - the entrant wage distribution - that was not a particular focus of Cahuc et al. (2006). I therefore choose to make a parametric assumption for the distribution of match quality, and assume it is log normal.

I must now show that I can identify the parameters of this log normal distribution i.e. the mean parameter, ζ_i^ν, the variance parameter, η_i^ν, and the lower bound, ν_{inf_i}. Recall that my estimation of these parameters is based on a SMM approach as summarized in equation (37), where $\underline{w_i}$ is the lowest wage in the wage distribution, $Q^{50}_{w_i}$ is the median wage and $\mathbb{E}^{F_{i,t}}(\nu)$ is the mean of the match quality sampling distribution, which will be targeted at a fixed value (I impose $\mathbb{E}^{F_{i,t}}(\nu) = 1$).

$$(\,\zeta_{i,t}^{\nu *}, \eta_{i,t}^{\nu *}, \nu_{inf_{i,t}}^{*}) = \underset{\zeta_{i,t}^{\nu},\eta_{i,t}^{\nu},\nu_{inf_{i,t}}}{\operatorname{argmin}} \ (m_t - \hat{m}_t)^T W (m_t - \hat{m}_t) \tag{37}$$

$$m_t \equiv \big(var_{\log(w_{i,t})}(\zeta_{i,t}^{\nu}, \eta_{i,t}^{\nu}, \nu_{inf_{i,t}}), \underline{w}_{i,t}(\nu_{inf_{i,t}})/Q^{50}_{w_{i,t}}(\zeta_{i,t}^{\nu}, \eta_{i,t}^{\nu}, \nu_{inf_{i,t}}), \\ \mathbb{E}^{F_{i,t}}(\nu)(\zeta_{i,t}^{\nu}, \eta_{i,t}^{\nu}, \nu_{inf_{i,t}})\big)$$

Proof of identification is hindered by the lack of tractability of the higher order moments of the wage distribution so I test whether my estimation procedure correctly identifies the true parameters of the model using Monte Carlo methods. That is I simulate a cross-section sample of wages for 50,000 workers (i.e. slightly less than the 60,000 that feature in the CPS) from the model with an arbitrary choice of parameters (the 'true' parameters). I then estimate the model using this simulated data to see if I recover the true parameters. Job contact rates, which also affect the cross-sectional distribution of workers wages, are set at their estimated values for the first year of my sample (1976) though the results of this exercise are not sensitive to their level.

Recall that I estimate the lower bound of the match quality distribution by targeting the ratio of the lower bound of wages in my sample relative to the median. As argued above this gives exact identification of the $\nu_{inf,i}$. I therefore feed the true parameter for the lower bound of the match quality into my estimation procedure directly, since it is exactly identified, rather than the minimum of simulated wages i.e. I set $\underline{w_{i,t}}/Q^{50}_{w_{i,t}}$ - the empirical moment I am targeting - to $\nu_{inf_{i,t}}/Q^{50}_{w^{sim}_{i,t}}$, where the superscript sim denotes simulated wage data.[25]

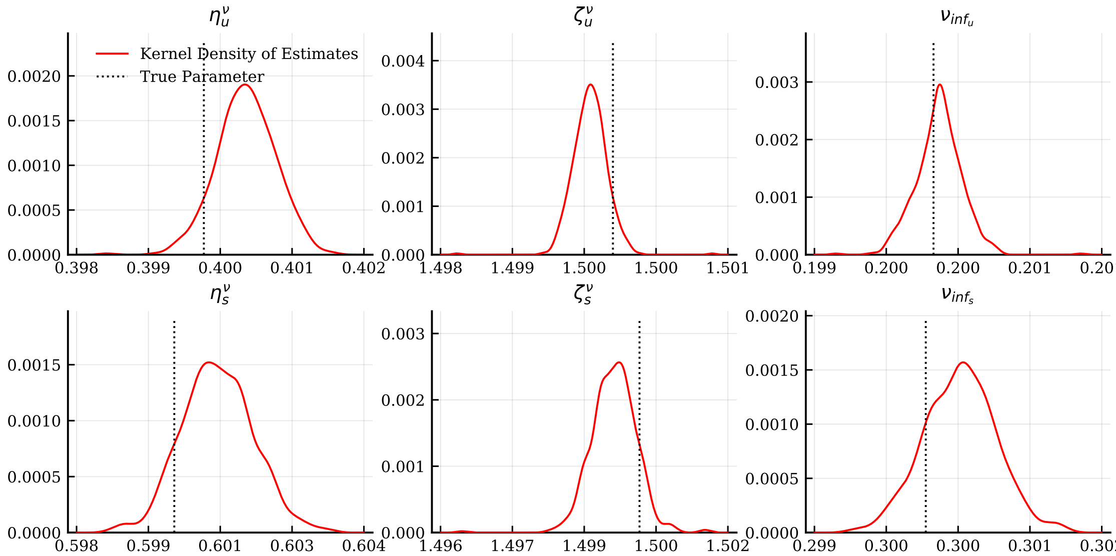
I estimate 500 sets of parameters corresponding to 500 simulations of data from the true model, producing the results shown in Figure 19. My estimation strategy is reasonably successful in recovering the true parameters, though not perfect: while there are some biases in the estimates, in each case they are very small in size.

Appendix C. Robustness

This section tests the robustness of parameter estimates of the KORV production function in my model to changes to my empirical strategy for estimating the parameters of the sequential auction model of the intermediate goods markets. In particular, I consider

[25] As in my actual empirical estimation of the sequential auction parameters, I normalize the price of the intermediate good, p_i, to one when performing the Monte Carlo test of identification.

FIGURE 19. Monte Carlo Analysis of Identification



Notes: The dotted line in each panel represents the true parameter value used to simulate data for estimation. 500 sets of data were simulated to generate 500 estimates for each parameter. The red line in each panel represents the kernel density of estimated parameter values. The top (bottom) row shows the variance parameter (η_i^ν), mean parameter (ζ_i^ν) and lower bound parameter $\nu_{inf,i}$ of the log normal match quality distribution for the unskilled (skilled) worker.

the impact of: (i) estimating the lower bound of the match quality distribution by targeting the average wage of workers in the first percentile of the wage distribution (rather than average wage of the bottom five percentiles) - see column 4 of Table 5, (ii) estimating the lower bound of the match quality distribution by targeting the average wage of workers in bottom two percentiles - see column 5, (iii) estimating the lower bound of the match quality distribution by targeting the minimum of the empirical wage distribution (after trimming, as is done in my baseline specification) - see column 6, (iv) estimating the variance parameter of the (log normal) sampling distribution of match quality by targeting residual wage variance, where I now control for age as well as race, sex and years of education in calculating this residual variance - see column 7, (v) estimating the variance parameter of the sampling distribution by targeting the interquartile range of residual log wages, rather than the variance - see column 8. None of these changes to my empirical strategy make a significant difference to my results, as illustrated in Table 5.

Table 5. KORV parameter values with frictions: robustness

(1) Parameter	(2) Without Frictions	(3) With Frictions: Baseline	(4)	(5)	(6)	(7)	(8)
λ	0.521	0.462	0.461	0.461	0.461	0.464	0.462
μ	0.442	0.462	0.451	0.533	0.512	0.508	0.594
α	0.127	0.118	0.118	0.118	0.118	0.118	0.118
γ	-0.202	-0.187	-0.185	-0.185	-0.184	-0.189	-0.185
σ	0.347	0.316	0.315	0.315	0.315	0.317	0.311
$\varepsilon_{S,K_{eq}}$ $(= 1/1 - \gamma))$	0.832	0.843	0.844	0.844	0.844	0.841	0.844
$\varepsilon_{U,K_{eq}}$ $(= 1/1 - \sigma))$	1.531	1.462	1.46	1.46	1.46	1.465	1.451
CSC Strength: $\varepsilon_{U,K_{eq}} - \varepsilon_{S,K_{eq}}$	0.699	0.619	0.616	0.616	0.616	0.624	0.607

Notes: Rows 2-6 show estimates of the primitive parameters of the KORV production function. Row 7 shows the implied elasticity of substitution between capital equipment and skilled labor input, $\varepsilon_{S,K_{eq}}$. Row 8 shows the implied elasticity of substitution between capital equipment and unskilled labor input, $\varepsilon_{U,K_{eq}}$. Row 9 shows the implied strength of the capital skill complementarity (CSC) channel, as measured by $\varepsilon_{U,K_{eq}} - \varepsilon_{S,K_{eq}}$.