Efficiency Wages and Inter-Industry Wage Differentials

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Abstract

Many empirical papers attribute a significant portion of inter-industry wage differentials to efficiency wage considerations. To evaluate this argument, I present a multi-industry shirking efficiency wage model and examine whether it is consistent with the data. With only small differences in detection rates the model is able to generate sizable and persistent differentials and account for the empirical findings that: (1) high-wage industries have higher profits-per-worker and capital-to-labor ratios, and (2) inter-industry wage differentials are acyclical. Interestingly, the model demonstrates that differences in worker ability may not help explain these differentials when firms only imperfectly observe their workers' effort levels.

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"An understanding of the nature of inter-industry wage differentials could prove quite useful in determining the relevance of alternative models of wage determination."

-Dickens and Katz (1987)

1. INTRODUCTION

The presence of persistent inter-industry wage differentials in developed countries has been well documented by Krueger and Summers (1987, 1988), Dickens and Katz (1987), Murphy and Topel (1987), Gera and Grenier (1995), and Blackburn and Neumark (1992). Standard competitive labor market models offer two common explanations for the presence of these differentials. First, firms in different industries may offer identical workers different wages to compensate for different non-pecuniary job attributes. These compensating differentials are paid to ensure that identical individuals enjoy equal utility levels. Second, workers with the same measurable attributes in different industries may receive different wages if there are systematic differences in unmeasured worker ability that are correlated with industry affiliation.

Although the competitive explanations appear promising, Blackburn and Neumark (1992), Krueger and Summers (1988), Dickens and Katz (1987), and Borjas and Ramey (2000) have cast some doubt on the ability of these competitive explanations to account for much of the observed inter-industry wage differentials.[1] Instead, many of these authors argue that efficiency wages can account for a large component of the wage differentials and may also provide an explanation for the empirical findings that high wage industries have higher

[1] Murphy and Topel's (1987) results are more supportive of the competitive labor model's unobserved ability explanation. However, even they found that on average approximately 30% of the estimated inter-industry wage differentials remained unaccounted for.

capital-to-labor ratios and higher profits per worker than low wage industries.[2] Despite their results and the microeconomic evidence that suggests there is a link between the level of monitoring, worker productivity and wages,[3] little work has focused on evaluating the ability of a multi-sector shirking efficiency wage model to explain the empirical regularities presence of persistent inter-industry wage differentials. Such an attempt is made in this paper using a general equilibrium framework. I demonstrate that the efficiency wage model is able to account for the empirical regularities as well as large and persistent inter-industry wage differentials. In addition, my results suggest that adding differences in worker ability may not help explain the differentials when firms face problems detecting shirking workers.

In the first part of the paper, the formal model is developed, then analyzed, to determine if it is qualitatively consistent with: *(i)* the behavior of the inter-industry wage differentials observed in the data, and *(ii)* the high wage-low wage industry differences mentioned above.[4] The new model has three main features. First, firms imperfectly observe the effort levels of their workers during the production process. Second, the firms' ability to detect shirking workers varies across sectors. Third, detected shirkers are assumed to forgo some compensation. Absent bonding, these features can generate equilibrium unemployment, and cause firms to choose different levels of effort, wages and employment in equilibrium. An examination of the model's properties indicate that the model performs well along both dimensions of interest. Specifically, the model predicts: (i) the presence of persistent inter-industry wage

[2] See Katz (1986) or Weiss (1990) for a good overview of the different efficiency wage models.

[3] The links between wages, monitoring and productivity at the firm level have been explored by Krueger (1991), Groshen and Krueger (1990), Levine (1992), and Rebitzer (1995) among others.

[4] For a good discussion of the evidence that high wage industries also tend to have high profits per worker and high capital per worker, see Dickens and Katz (1987).

differentials, and (*ii*) that high wage industries have higher capital per worker and higher profits per worker than low wage industries.

After the properties of the baseline model are presented, I examine how the addition of differences in worker's ability may affect the results. I consider two ways of modeling worker ability. In the first case, I assume that the worker's ability affects the amount of effective labor that is provided to firms. In the second case, I assume that individuals with higher ability will have lower costs associated with providing effort on the job. This exercise yields an interesting set of results. The model with differences in worker ability is consistent with the observation that high ability workers are more often employed in high wage industries. However, the model demonstrates that, when firms cannot perfectly monitor their employees effort, large inter-industry wage differentials cannot be attributed to the differences in worker ability.[5]

In the second part of the paper, I calibrate the model to determine how large the differences in detection rates must be to obtain large inter-industry wage differentials. Using data from the Current Population Survey (CPS), I estimate the interindustry wage differentials for the years 1973-1999. These estimates are used to determine the size and behavior of the inter-industry wage differentials in the U.S., and calibrate the model. Two striking results emerge from this exercise. First, according to the model, small differences in the detection rates are able to produce significant and persistent inter-industry wage differentials. Second, the inter-industry wage differentials predicted by the model are consistent with my empirical finding that the inter-industry wage differentials estimated from the CPS data are generally

[5] These results are generally consistent with Gibbons and Katz's (1992) findings that while workers' traits influence their mobility, they only have a small or nonexistent direct impact on their wages.

acyclical.[6]

All shirking efficiency wage models, including the one present here, are based on Shapiro and Stiglitz's (1984) model in which a positive link exists between a worker's effort and his wage because firms imperfectly observe the effort levels of their workers.[7] Individuals provide their contractual level of effort at the offered wage only if the expected utility of providing the effort is greater than or equal to the expected utility associated with shirking, (i.e., they will abide by the terms of their contracts if their incentive compatibility constraints are satisfied). Therefore, profit maximizing firms take the incentive compatibility constraints of their workers into account when choosing the terms of their employees' contracts, as well as the amounts of capital and labor they will employ during the period.

Real wages and employment levels in shirking models are determined by the interaction of the individuals' incentive compatibility constraints and labor demand - not the interaction between labor demand and labor supply as in the standard labor market clearing models. It follows that, if firms in different industries do not face identical monitoring problems, the incentive compatibility constraints of identical workers and the wages firms will offer them will vary across industries. Consequently, a multi-sector shirking efficiency wage model may offer a compelling explanation as to why the compensation of identical workers differs across industries.

In a novel attempt to determine if inter-industry wage differentials can be attributed to shirking efficiency wage considerations, Walsh (1999) analyses a multi-sector shirking

[6] This result is consistent with Keane's (1993) findings using the National Longitudinal Survey of Young Men for the years 1966-1981.

[7] Examples include Albrecht and Vroman (1992, 1999), Gomme (1999), and Walsh (1999).

efficiency wage model based on the original Shapiro-Stiglitz model where firms in different industries detect shirkers with different probabilities, and detected shirkers are fired. Based on this setup, he concludes that small differences in detection rates cannot produce the large wage differentials attributed to the efficiency wage models in the empirical literature.

Although the methodology in Walsh's (1999) paper is appealing, it is well known that: *(1)* the type of Shapiro-Stiglitz model used in his investigation has problems matching important features of the economy such as the behavior of wages and employment over the business cycle, and *(2)* these problems are attributable to the assumption that detected shirkers are fired in the model.[8] Consequently, in this paper I explore the robustness of Walsh (1999) conclusions by developing and analyzing a different style of shirking model. In the multi-sector model I examine, detected shirkers are not dismissed but instead forgo a portion of their compensation. I opt to use a model that embeds this alternative "monetary punishment" for two reasons. First, past work has demonstrated that a general equilibrium shirking efficiency wage model with this type of punishment is better able to account for the low wage variation and high variation in employment seen in the U.S. data than standard business cycle models.[9] Second, the new model is more consistent with survey evidence that suggests firms more commonly rely on this type of "monetary punishment" to discipline workers than on outright dismissal.[10] The stark difference between Walsh's (1999) findings,

[8] See e.g., Gomme (1999).

[9] Papers such as Alexopoulos (2004, 2007), Burnside, Eichenbaum and Fisher (2000), and Felices (2001) examine the responses of this type of shirking efficiency wage model to shocks.

[10] Evidence in Agell and Lungborg (1995), Hall (1993), and Malcomson (1998), suggests that firms do not immediately fire detected shirkers. Instead, it is more common to reprimand detected shirkers, and remove opportunities from them that will result in monetary costs (e.g., lower bonuses or raises). In addition Bewley (1999) provides evidence that a number of firms tend to use bonuses and wage increases to motivate their workers.

and the results presented in this paper are attributable to the differences in the models' punishments associated with shirking.

The remainder of the paper is organized as follows. Section 2 develops a multi-industry shirking efficiency wage model where detected shirkers forgo a bonus. Section 3 investigates the properties of this model to determine if they are consistent with: *(i)* persistent inter-industry wage differentials, and *(ii)* the empirical evidence about the links between wages and industry characteristics. In Section 4, an empirical analysis of the inter-industry wage differentials is presented, and Section 5 concludes the paper.

2. THE BASIC MODEL

The model economy is composed of four sectors. The first sector contains families and their members; the second sector is comprised of perfectly competitive final good firms; and the last two are made up of two monopolistically competitive intermediate good industries. Each sector's problem is discussed in detail below. For simplicity, I focus on the case where there are only 2 industries in the economy. However, it is simple to extend the model to allow for a finite number of different industries in the economy, and demonstrate that all of the results described in Section 3 can be generalized.

2.1. The Representative Family and its Members' Problem

Whenever there is a positive level of unemployment in equilibrium, if workers' income levels are not perfectly insured and individuals can transfer wealth between periods, the workers' problems become heterogeneous. In this model, the workers' problems are kept homogeneous by introducing a family construct.[11] Here it is assumed that workers cannot

[11] The properties of the model below are not significantly affected if, instead of having workers belonging

transfer wealth across periods, but their families can. Since some of the returns on assets are distributed to the family members, individuals' consumption levels are partially insured by their family. However, any one individual's employment status does not affect the savings decisions in the family, and when individuals make their decisions, the workers take as given the amount of consumption they expect to receive from their family.

The descriptions of the family and the family's problem are similar to the ones outlined in Alexopoulos (2007, 2004), Nakajima (2006), Burnside, Eichenbaum and Fisher (2000), and Felices (2001). There are two main assumptions. First, there are a large number of identical families, each of which contain a (0,1)-continuum of identical members. Second, the families own all of the assets in the economy. Each family owns an equal share of the economy wide capital stock and an equal portion of firms' stocks in each industry. As a result, each family is entitled to a fraction of each firm's profits.

In this model, the representative family must choose how much of its period t income (i.e., return on capital, $r_t^1 K_t^1 + r_t^2 K_t^2$, and profits from the different sectors, $\pi_t^1 + \pi_t^2$) to spend on investment in capital goods for each industry, I_t^1 and I_t^2, and how much to spend on final goods for their members to consume, c_t^f. This implies the following budget constraint for the family:

$$r_t^1 K_t^1 + r_t^2 K_t^2 + \pi_t^1 + \pi_t^2 \geq c_t^f + (K_{t+1}^1 - (1-\delta)K_t^1) + (K_{t+1}^2 - (1-\delta)K_t^2) \tag{1}$$

where δ is the depreciation rate of capital, K_t^j is the capital rented to industry $j \in \{1,2\}$ and r_t^j is the rental rate of capital in industry $j \in \{1,2\}$. The family chooses the levels of

to a family, it is assumed that there are two types of agents in the economy: entrepreneurs and workers. Similar to the environment seen in Gomme (1999), each worker would be unable to accumulate capital but would be endowed with some of the firms' shares, while each entrepreneur would be able to accumulate capital and would own the majority of shares in a firm.

I_t^1, I_t^2 and c_t^f to maximize the expected discounted value of its lifetime utility subject to its budget constraint.[12]

2.1.1. Family Members

Individuals are assumed to have log-separable utility functions. The utility levels of individual family members employed in industry j and : *(i)* not shirking, *(ii)* shirking and detected, and *(iii)* shirking and not detected, are respectively:

$$U(c_t^j, e_t^j) = \ln(c_t^j) + \gamma \ln(T - \vartheta(e_t^j > 0)(e_t^j + \xi)) \tag{2}$$

$$U(c_t^{sj}, 0) = \ln(c_t^{sj}) + \gamma \ln(T) \tag{3}$$

$$U(c_t^j, 0) = \ln(c_t^j) + \gamma \ln(T) \tag{4}$$

where $\gamma > 0$, T is the individual's time endowment, e_t^j is the amount of effort the individual exerts on the job in industry $j \in \{1, 2\}$, and ξ is the fixed cost associated with providing any effort on the job.[13] ,[14] In addition, $\vartheta(\cdot)$ is an indicator function that takes on the value 1 if the individual provides any positive level of effort and 0 otherwise. Further, c_t^j, and c_t^{sj} denote the consumption levels of workers in industry j not detected shirking, and the consumption levels of workers in industry j who are detected shirking respectively, where $j \in \{1, 2\}$. An unemployed family member has a consumption level of c_t^u and a utility level of:

$$U(c_t^u, 0) = \ln(c_t^u) + \gamma \ln(T) \tag{5}$$

[12] To keep the environment as simple as possible, following Phelps (1994), I assume that families do not believe that their choices can affect the employment probability of their members. However, Alexopoulos (2004b) provides assumptions that rationalize this assumption and leads to precisely the same allocations as in this model.

[13] For simplicity, the notation that separates the actual effort provided and the level of effort specified in the firms' contracts is suppressed in the discussion since they are equal in equilibrium.

[14] To sharply focus on the effect of different detection rates, I assume that ξ is the same across jobs in the baseline model.

The consumption of each of the family members during the period depends on their job market outcomes. Each member will either be: *(i)* employed in industry 1, *(ii)* employed in industry 2, or *(iii)* unemployed. In addition to the consumption differences caused by different employment statuses, workers' consumption levels can differ depending on whether or not they are detected shirking on the job.

In this simple version of the model, it is assumed that firms hire workers using a one period contract where a fraction, s, of a worker's possible wage during the period is paid to all workers while the remaining fraction, $(1-s)$, of the total possible wage is only paid to workers not detected shirking during the period.[15,16] Consistent with the empirical evidence in surveys such as the Sage System Administrator Salary Profile (1999) and the International Consumer Service Association Incentive and Bonus Survey (2001), I assume that s is the same across industries. In addition, firms are assumed not to punish workers not detected shirking. These assumptions are made solely for simplicity. The results in this paper are unaffected if the model instead assumes: *(i)* there are continuing matches between workers and firms that breakup with an exogenous probability, *(ii)* a firm gets a reputation as a bad employer if it does not pay the bonus to non-detected shirkers, *(iii)* workers will not provide effort to bad employers because they believe that bad employers will fail to provide them

[15] In this case, we can interpret sw_t^i as a base wage or salary, that is guaranteed to the worker, and $(1-s)w_t^i$ as a bonus payment.

[16] Although s is an exogenous parameter here, a constant positive value of s can be endogenously generated in this type of model when firms make mistakes when detecting shirking behavior (See Alexopoulos (2004b)).

with their bonus, and *(iv)* there are reasonable levels of markups in the economy.[17,18]

Letting N_t^j denote the number of workers employed in industry j, for $j \in \{1,2\}$, the consumption levels for non disciplined workers in industry j, detected shirkers in industry j and unemployed family members are:

$$c_t^j = w_t^j - Tr_t + c_t^f \tag{6}$$

$$c_t^{sj} = sw_t^j - Tr_t + c_t^f \tag{7}$$

$$c_t^u = \frac{N_t^1 + N_t^2}{(1 - N_t^1 - N_t^2)} Tr_t + c_t^f \tag{8}$$

Here, w_t^j is the real wage paid to individuals employed in industry j, and Tr_t is the amount of transferred by each employed worker to their family's unemployment insurance fund.[19] In this simple case, the unemployment insurance funds ensure that the unemployed members enjoy the same utility as detected shirkers in the low wage industry. Consequently,

$$Tr_t = \min(sw_t^1, sw_t^2)(1 - N_t^1 - N_t^2) \tag{9}$$

In equilibrium, the model predicts that wages will be lower in the high detection industry and effort will be higher (See Propositions 2 and 3 below). Therefore, this transfer level will imply that unemployed workers are involuntarily unemployed in equilibrium.[20] Although, assumptions about the intra-family transfer will have an affect on the dynamics of the model

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[17] An examination of this richer environment demonstrates that when $\beta = \left(\frac{1}{1.03}\right)^{\frac{1}{4}}$ and $\mu > 1.01$, the firm has no incentive to withhold bonuses from non-detected shirkers. As a result, the firm's problem will reduce back to a one period problem and, since the probability that the match breaks up is exogenous, the individual's incentive compatibility constraints are the same as those in the simple version of the model.

[18] See Basu and Fernald (1994,1997) for some evidence on markups in the U.S. economy.

[19] This unemployment insurance could easily be modeled as being handled by the government, instead of the family.

[20] When the detection rate in industry 1 is less than the detection rate in industry 2 (i.e., $d_1 < d_2$), $e^1 < e^2$ and $w^1 > w^2$. Given these inequalities and the fact that the transfer is $Tr_t = sw_t^2(1 - N_t^1 - N_t^2)$, $c^{s1} > c^{s2} = c^u$. Since firms choose the terms for their contracts so that no one shirks in equilibrium, it follows

and will affect whether or not the unemployed family members are voluntarily or involuntarily unemployed, this assumption will not effect the theoretical properties of the model developed in the next section.[21]

2.2. The Family's Problem

Letting N_t^{sj} denote the number of shirking family members hired in industry j, and letting d_j denote the probability a shirker is detected by a firm in industry j, the family's problem can be expressed as:

$$\max_{\{K_{t+1}^1, K_{t+1}^2, c_t^f\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t \left\{ \begin{array}{c} [(N_t^1 - N_t^{s1})\, U(c_t^1, e_t^1) + (1-d_1) N_t^{s1} U(c_t^1, 0) + d_1 N_t^{s1} U(c_t^{s1}, 0)] \\ +\, [(N_t^2 - N_t^{s2})\, U(c_t^2, e_t^2) + (1-d_2) N_t^{s2} U(c_t^2, 0) + d_2 N_t^{s2} U(c_t^{s2}, 0)] \\ +(1 - N_t^1 - N_t^2) U(c_t^u, 0) \end{array} \right\}$$

subject to equation (1), where $c_t^j, c_t^{sj}, c_t^u, U(c_t^j, e_t^j), U(c_t^{sj}, 0), U(c_t^j, 0)$ and $U(c_t^u, 0)$ are described by equations (2)-(9) respectively.

Profit maximizing firms ensure that no one shirks in equilibrium. Furthermore, $r_t^1 = r_t^2 = r_t$ for capital to be employed in both industries. It follows that, in equilibrium,

$$E_t \left\{ \left[\frac{N_t^1}{c_t^1} + \frac{N_t^2}{c_t^2} + \frac{1 - N_t^1 - N_t^2}{c_t^u} \right] - \beta \left[\frac{N_{t+1}^1}{c_{t+1}^1} + \frac{N_{t+1}^2}{c_{t+1}^2} + \frac{1 - N_{t+1}^1 - N_{t+1}^2}{c_{t+1}^u} \right] ((1-\delta) + r_{t+1}) \right\} = 0$$

where the marginal utility of the family at time t is a weighted average of the marginal utility of the different types of family members, i.e., $\frac{N_t^1}{c_t^1} + \frac{N_t^2}{c_t^2} + \frac{1-N_t^1-N_t^2}{c_t^u}$.

2.3. Final Good Firms

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from the individuals' incentive compatibility constraint that:

$$U(c_t^1, e_t^1) > U(c_t^2, e_t^2) = d_2 U(c_t^{s2}, 0) + (1 - d_2) U(c_t^2, 0) > U(c_t^u, 0)$$

because the individuals' utility function, $U(c, e)$, is increasing in c and decreasing in e. Therefore, unemployed individuals have a lower utility level than their working counterparts and these individuals are involuntarily unemployed in equilibrium.

[21] For a discussion about how changes in the levels of unemployment insurance affects the quantitative properties in a similar model with only one sector, see Alexopoulos (2004) or Felices (2001).

Firms in the final goods sector are perfectly competitive and produce the final good, Y_t, using output from the intermediate goods firms as inputs according to the following production function:

$$Y_t = \left(a_1 \left(\int_0^1 Y_t^1(i)^{\frac{1}{\phi}} di \right)^{\frac{\phi}{\mu}} + a_2 \left(\int_0^1 Y_t^2(i)^{\frac{1}{\phi}} di \right)^{\frac{\phi}{\mu}} \right)^{\mu}$$

Here $\mu \geq 1, \phi \geq 1$, and $Y_t^1(i)$ and $Y_t^2(i)$ are the goods from intermediate goods firm i in industry 1 and 2 respectively. The representative final good firm's problem can be written as:

$$\max_{Y_t, \left\{Y_t^1(i)\right\}_0^1, \left\{Y_t^2(i)\right\}_0^1} Y_t - \int_0^1 P_t^1(i) Y_t^1(i) di - \int_0^1 P_t^2(i) Y_t^2(i) di$$

where $P_t^1(i)$ and $P_t^2(i)$ are the prices for intermediate goods from firm i in industry 1 and 2 respectively normalized by the price of the final good. Combining the first order necessary conditions, and the zero profit conditions yields the following equations:

$$Y_t^j(i) = a_j^{\frac{\mu}{\mu-1}} Y_t (\overline{P}_t^j)^{\frac{\mu-\phi}{(\mu-1)(\phi-1)}} P_t^j(i)^{\frac{-\phi}{\phi-1}} \text{ and } \left\{ a_1^{\frac{\mu}{\mu-1}} \left(\overline{P}_t^1 \right)^{\frac{-1}{\mu-1}} + a_2^{\frac{\mu}{\mu-1}} \left(\overline{P}_t^2 \right)^{\frac{-1}{\mu-1}} \right\}^{1-\mu} = 1$$

where $\overline{P}_t^j = \left[\int_0^1 P_t^j(i)^{\frac{-1}{\phi-1}} di \right]^{1-\phi}$ for $j = 1, 2$.

For the remainder of the paper the following notation is used: $Y_t^1 = \int_0^1 Y_t^1(i) di$, $Y_t^2 = \int_0^1 Y_t^2(i) di$ and $y_t = \frac{Y_t^2}{Y_t^1}$. It is also assumed that all firms in an industry are symmetric and $a_1 = a_2 = 1$. It follows that:

$$\frac{P_t^1}{P_t^2} = \frac{P_t^1(i)}{P_t^2(i)} = y_t^{\frac{\mu-1}{\mu}}$$

Therefore, as the size of industry 1 increases relative to industry 2, y_t decreases and the price of goods in industry 1 falls relative to the price of goods in industry 2.

2.4. The Intermediate Goods Firms

In this economy, there are two different industries (sectors) containing intermediate goods firms. Entry of new firms over time is ruled out and no firms are able to switch industries.

The intermediate goods firms in both industries are monopolistic competitors and require effort from their employees in order to produce goods during the period. Since effort is only imperfectly observed, firms will choose to offer workers a contract that will satisfy their incentive compatibility constraint. Given the level of the family's transfers to their unemployed members, workers will always accept employment from firms and the individuals' rationality constraints never bind. As a result, the relationship between a worker's wage and his effort level will be determined by the fact that firms will make workers just indifferent between shirking on the job and providing the profit maximizing effort level specified in the contract.

Based on the demand function from the final good firms, the exogenous detection rate, d_j, and the fact that the workers' incentive compatibility constraints hold with equality in equilibrium, the monopolistically competitive firm's problem can be expressed as:

$$\max_{\{K_t^j, N_t^j w_t^j, P_t^j\}} P_t^j Y_t^j - r_t^j K_t^j - w_t^j N_t^j \quad \textit{subject to}$$

$$N_t^j \leq x_t^j$$

$$Y_t^j = \theta_t^j (K_t^j)^{\alpha} (e_t^j N_t^j)^{1-\alpha}$$

$$e_t^j = T\left(1 - \left(\frac{c_t^j}{c_t^{sj}}\right)^{-\frac{d_j}{\gamma}}\right) - \xi$$

$$Y_t^j = Y_t (\overline{P}_t^j)^{\frac{\mu-\phi}{(\mu-1)(\phi-1)}} P_t^{j\,\frac{-\phi}{\phi-1}}$$

where N_t^j and K_t^j are the number of people hired and the amount of capital rented respectively, x_t^j is the number of people who are looking for work at the representative firm in industry j and θ_t^j is the level of technology in industry j.[22] Since there is unemployment in the U.S.

[22] Although there is only one type of job in this model, in the companion paper, Alexopoulos (2005), I

economy, the remainder of the paper will focus on the model's results for the case when firms in neither sector are constrained by the number of employees looking for work, (i.e., the case where $x_t^1 > N_t^1$ and $x_t^2 > N_t^2$). In this case, the first order necessary conditions for industry j, can be written as:

$$\frac{e_{w_t^j}(w_t^j)}{e(w_t^j)} w_t^j = 1 \textit{ (Solow Condition)}$$

$$\frac{(1-\alpha)}{\phi} \frac{P_t^j Y_t^j}{N_t^j} - w_t^j = 0$$

$$\frac{\alpha}{\phi} \frac{P_t^j Y_t^j}{K_t^j} - r_t = 0$$

$$\text{where } e_t^j = e(w_t^j) = T\left(1 - \left(\frac{c_t^j}{c_t^{sj}}\right)^{-\frac{d_j}{\gamma}}\right) - \xi \text{ and } e_{w_t^j}(w_t^j) = \frac{\partial e(w_t^j)}{\partial w_t^j}$$

assuming firms are symmetric within industries. Using the fact that $w_t^j, e_{w_t^j}(w_t^j)$ and $e(w_t^j)$ can be expressed as functions of c_t^j and c_t^{sj}, the Solow condition implies that wages are chosen such that the ratio $\frac{c_t^j}{c_t^{sj}}$ is a constant greater than one, (i.e., the consumption of non-shirkers is greater than the consumption of detected shirkers), and effort is constant across all states of the world and across time, (i.e., $e_t^j = e^j$).

3. PROPERTIES OF THE MODEL WITH UNEMPLOYMENT

In this section, I examine the properties of the model and demonstrate they are consistent with evidence which suggests that: (1) inter-industry wage differentials are persistent, (2) firms' with a lower probability of detecting shirking workers pay higher wages, (3) high wage industries have higher capital-to-labor ratios and higher profits per worker than low wage industries, and (4) workers may queue for jobs in the high wage industry.

demonstrate how an extended version of this model can account for the high correlation of workers' wages within the industry even when the effort of only one type of worker is imperfectly observable.

3.1. Wages and Effort in the Different Industries

The Solow conditions for the firms in different industries imply that wages will be chosen so that consumption of the non-shirkers is directly proportional to the consumption of the detected shirkers since:

$$\frac{c_t^j}{c_t^{sj}} = \Pi_j \text{ for } j \in \{1, 2\}$$

This equation allows us to derive the following expressions for wages:

$$w_t^j = \frac{(\Pi_j - 1)(c_t^f - Tr_t)}{(1 - s\Pi_j)} \text{ for } j \in \{1, 2\}$$

which implies:

$$\frac{w_t^1}{w_t^2} = \frac{(1 - s\Pi_2)(\Pi_1 - 1)}{(1 - s\Pi_1)(\Pi_2 - 1)} = \mathcal{D}$$

where $\mathcal{D}$ is the inter-industry wage differential. Clearly, since this differential only depends on the parameters that affect the individuals' incentive compatibility constraint, (i.e., s, d_j, γ, T, and ξ) the model predicts that $\mathcal{D}$ will be very persistent over time and across different states of the world. As a result, the model is consistent with Krueger and Summer's (1988) empirical findings about the behavior of inter-industry wage differentials in the U.S.

Although, the model can predict a persistent differential, it remains to be demonstrated that $\mathcal{D} > 1$ (i.e., that model predicts lower detection rates coincide with higher wages). Propositions 1 and 2 confirm this is indeed the case. [23]

Proposition 1: Firms will offer workers a contract that ensures that the consumption of non-shirking workers relative to the consumption of detected shirkers in the industry increases as the probability of detecting a shirker decreases, (i.e., $\Pi_1 > \Pi_2$ when $d_1 < d_2$).

[23] The proof for this proposition, and all others, are provided in Appendix A.

This result can be formally proven using the assumption that the value of the constants, Π_j are not much larger that 1, and the Solow condition. Intuitively, it implies that, as the detection rate drops, firms must increase the punishment associated with detection (i.e., increase the wage of non-shirkers relative to the wage of detected shirkers) in order to prevent workers from shirking on the job.

The fact that $\Pi_1 > \Pi_2$ and $w_t^1 > w_t^2$ when $d_1 < d_2$ would be trivial to show if all firms in the economy require the same level of effort regardless of their detection rate.[24] However, in this model, firms in industries with low detection rates have the option to offer a contract with lower levels of e_t and w_t than high detection firms if they find it profitable to do so. Specifically, as the detection rate decreases, the expected utility of shirking increases for a given wage and effort pair. To prevent shirking, firms can satisfy the individual's incentive compatibility constraint by: *(i)* leaving the wage unchanged and reducing the required effort level, *(ii)* raising the wage and leaving the effort level unchanged, or *(iii)* raising wages and lowering the required effort. The firm's first order conditions imply that as the detection rate changes, profit maximizing firms will adjust both wages and effort levels. Therefore, the results reported in Propositions 2 and 3 confirm that real wages will be higher in industries/firms that cannot detect shirkers easily[25] and firms in the low detection industry will require less effort than firms in the high detection industry

Proposition 2: In this economy, workers in the low detection industry will be paid a higher wage than workers in a high detection industry, (i.e., $\frac{w_t^1}{w_t^2} = \mathcal{D} > 1$).

[24] If all firms required the same effort level, the individuals IC constraints imply $\Pi_1^{d_1} = \Pi_2^{d_2}$. Therefore, $\left(\frac{c_t^1}{c_t^{s1}}\right) > \left(\frac{c_t^2}{c_t^{s2}}\right)$ and $w_t^1 > w_t^2$.

[25] This result is consistent with Krueger's (1991) and Groshen and Krueger's (1990) work that finds wages are higher in firms that have more difficulty detecting shirking workers.

Proposition 3: The contractual effort rate decreases as the probability of detection decreases, (i.e., $e^1 < e^2$ when $d_1 < d_2$).

3.2. The Relative Size of the Industries

From the firms' first order necessary conditions, we can also determine the relative size of the industries. Given that there are positive levels of capital rented by firms in both industries, the relationship between the industries' ratios of capital-to-labor can be expressed as:

$$\frac{\alpha}{\phi}\frac{P_t^1 Y_t^1}{K_t^1} = \frac{\alpha}{\phi}\frac{P_t^2 Y_t^2}{K_t^2} \Rightarrow \frac{\frac{K_t^1}{N_t^1}}{\frac{K_t^2}{N_t^2}} = \left(\frac{P_t^1}{P_t^2}\frac{\theta_t^1}{\theta_t^2}\right)^{\frac{1}{1-\alpha}}\frac{e^1}{e^2}$$

Then, using the fact that $\frac{w_t^1}{w_t^2} = \mathcal{D}$ it follows that:

$$\mathcal{D} = \frac{P_t^1}{P_t^2}\frac{\theta_t^1}{\theta_t^2}\left(\frac{\frac{K_t^1}{N_t^1}}{\frac{K_t^2}{N_t^2}}\right)^{\alpha}\left(\frac{e^1}{e^2}\right)^{1-\alpha} \Rightarrow \mathcal{D} = \left(\frac{P_t^1}{P_t^2}\frac{\theta_t^1}{\theta_t^2}\right)^{\frac{1}{1-\alpha}}\left(\frac{e^1}{e^2}\right) \Rightarrow \frac{P_t^1}{P_t^2} = \left(\frac{e^2}{e^1}\mathcal{D}\right)^{1-\alpha}\frac{\theta_t^2}{\theta_t^1}$$

Since $\frac{P_t^1}{P_t^2} = y_t^{\frac{\mu-1}{\mu}}$, it is clear that:

$$y_t = \left[\left(\frac{e^2}{e^1}\mathcal{D}\right)^{1-\alpha}\frac{\theta_t^2}{\theta_t^1}\right]^{\frac{\mu}{\mu-1}}$$

As a result, the relative size of the industries is:

$$\frac{P_t^1 Y_t^1}{P_t^2 Y_t^2} = y_t^{\frac{-1}{\mu}} = \left[\left(\frac{e^2}{e^1}\mathcal{D}\right)^{1-\alpha}\frac{\theta_t^2}{\theta_t^1}\right]^{\frac{-1}{\mu-1}}$$

Therefore, as $\frac{\theta_t^2}{\theta_t^1}$ increases, industry one decreases in size relative to industry 2. Also, if $\frac{\theta_t^2}{\theta_t^1}$ is constant, y_t is constant and the relative size of the industry remains unchanged over time.

3.3. The Capital-to-Labor Ratio, and the Relative Size of Capital and Employment in the Industries

The work presented in Dickens and Katz (1987) show that high wage industries tend to have higher capital-to-labor ratios than low wage industries. The model is also consistent with this empirical regularity. In particular, the firms' Euler equations imply that $\frac{K_t^i}{N_t^i} = \frac{w_t^i \alpha}{r_t(1-\alpha)}$ for $i = 1, 2$. Therefore, it follows that $\frac{\frac{K_t^1}{N_t^1}}{\frac{K_t^2}{N_t^2}} = \mathcal{D} > 1$ with difference in the size of the ratio increasing with the size of the wage differential.

In addition to examining the relationship between the capital-to-labor ratio and the size of the wage differential, $\mathcal{D}$, it is possible to determine the relationship between $\mathcal{D}$ and the relative size of employment and capital in the two industries. The firms' Euler equations can be rearranged to confirm $\mathcal{D} = \frac{P_t^1}{P_t^2}\frac{Y_t^1}{Y_t^2}\frac{N_t^2}{N_t^1}$. This, in turn implies that $\frac{N_t^2}{N_t^1} = \mathcal{D} y_t^{\frac{1}{\mu}}$ (using the fact that $\frac{P_t^1 Y_t^1}{P_t^2 Y_t^2} = y_t^{\frac{-1}{\mu}}$) and $\frac{K_t^1}{K_t^2} = \mathcal{D}\frac{N_t^1}{N_t^2} = y_t^{\frac{-1}{\mu}}$ (given $\frac{K_t^1}{N_t^1} = \mathcal{D}\frac{K_t^2}{N_t^2}$). As a result if $\theta_t^1 = \omega \theta_t^2$, for all t where ω is a constant, then $y_t = y$ and the levels of employment and capital in the different industries are always proportional. However, if sector 2 becomes relatively more productive than sector 1, $\frac{\theta_t^2}{\theta_t^1}$ increases and sector 2 will employ relatively more capital and labor (i.e., $\frac{N_t^2}{N_t^1}$ and $\frac{K_t^2}{K_t^1}$ rise).

Finally, Proposition 4, describes the model's predictions about how a change in the detection rate in industry 1 affects the steady state levels of employment.

Proposition 4: A decrease in the detection rate in industry 1 relative to the detection rate in industry 2 causes employment in industry 1 to fall, and causes employment in industry 2 to rise in steady state.

3.4. Profit Rates

The empirical work discussed in Dickens and Katz (1987) also suggests that there is a correlation between industry characteristics and profit rates. Specifically, high wage industries tend to have higher profit rates than low wage industries. The model is also able to reproduce this relationship. When the profit rate is defined as the amount of profit per worker, the Euler equations imply that:

$$\frac{\pi_t^1}{\pi_t^2}\frac{N_t^2}{N_t^1} = \frac{P_t^1 Y_t^1 - r_t K_t^1 - w_t^1 N_t^1}{P_t^2 Y_t^2 - r_t K_t^2 - w_t^2 N_t^2}\frac{N_t^2}{N_t^1} = \frac{P_t^1 Y_t^1 \left(1 - \frac{\alpha}{\phi} - \frac{1-\alpha}{\phi}\right)}{P_t^2 Y_t^2 \left(1 - \frac{\alpha}{\phi} - \frac{1-\alpha}{\phi}\right)}\frac{N_t^2}{N_t^1} = y_t^{-\frac{1}{\mu}} \mathcal{D} y_t^{\frac{1}{\mu}} = \mathcal{D} > 1$$

Therefore, the model predicts that firms in the low detection industry (high wage industry) will have higher profits per worker than firms in the high detection industry (low wage industry). This does not, however, imply that total profits will be are higher in the low detection industry. For example, if $\frac{\theta_t^2}{\theta_t^1} = 1$, in equilibrium:

$$y_t = y = \left[\frac{e^2}{e^1}\mathcal{D}\right]^{\frac{\mu(1-\alpha)}{\mu-1}} > 1$$

In this case, $\frac{\pi_t^1}{\pi_t^2} = y_t^{-\frac{1}{\mu}} < 1$ and profits would be higher in the industry with lower wages, (i.e., industry 2). However, if $\frac{\theta_t^2}{\theta_t^1} \neq 1$, it is possible for $\frac{\pi_t^1}{\pi_t^2} = y_t^{-\frac{1}{\mu}} > 1$ causing profits to be higher in the low detection industry. Consequently, which industry earns the higher profits will depend on the relative levels of technology in the industries.

3.5. Relative Prices

In the model, the relative prices of goods in the two industries are:

$$\frac{P_t^1}{P_t^2} = y_t^{\frac{\mu-1}{\mu}}$$

Therefore, as y_t increases (i.e., $\frac{\theta_t^2}{\theta_t^1}$ increases), then the price of industry 1's output increases relative to the price of the output in industry 2.

3.6. The Industries' Labor Forces

The previous results are derived under the condition that $x_t^j > N_t^j$. However, to this point there has been no discussion about how x_t^i is determined. Here, I examine the sizes of the industries' labor forces and the size of their job queues under two different assumptions. In the first case, I assume that workers are free to look for work in both sectors simultaneously while in the second case I assume that workers can search in only one sector at a time.

Case 1: If individuals are free to look for work in both sectors simultaneously, all workers will look for jobs in both sectors since there is no cost to searching. However, workers will prefer to be employed in industry 1 rather than in industry 2, since wages are higher and effort is lower. As a result, all workers would accept a job from a firm in industry 1, while only workers without a job offer from industry 1 would accept employment offers from industry 2. Therefore, when workers are free to look in both sectors simultaneously, industry 1 will have a larger pool of potential employees than firms in industry 2.

Case 2: If workers can only look for employment in one industry during the period, then $x_t^1 + x_t^2 = 1$. Further, an individual going to industry 1 must have the same expected utility as a worker seeking employment from industry 2 in equilibrium, since workers can search in either industry. Consequently, the economy's equilibrium market clearing condition is:

$$\frac{N_t^1}{x_t^1}U(c_t^1, e_t^1) + \left(1 - \frac{N_t^1}{x_t^1}\right)U(c_t^u, 0) = \frac{N_t^2}{x_t^2}U(c_t^2, e_t^2) + \left(1 - \frac{N_t^2}{x_t^2}\right)U(c_t^u, 0)$$

$$\text{which implies } x_t^1 = \frac{f_0}{f_1 \frac{N_t^2}{N_t^1} + f_0} \text{ and } x_t^2 = 1 - x_t^1$$

$$\text{where } f_0 = \ln\left(\frac{c_t^1}{c_t^u}\right) + \gamma \ln\left(\frac{T - e^1 - \xi}{T}\right) \text{ and } f_1 = \ln\left(\frac{c_t^2}{c_t^u}\right) + \gamma \ln\left(\frac{T - e^2 - \xi}{T}\right)$$

Changes in x_t^1 depend solely on changes in $\frac{N_t^2}{N_t^1}$ since effort levels in the different industries are constant across time and across states of the world, and:[26]

$$\ln\left(\frac{c_t^2}{c_t^u}\right) = \ln\left(\frac{c_t^2}{c_t^{s2}}\right) = \ln(\Pi_2) \text{ and } \ln\left(\frac{c_t^1}{c_t^u}\right) = \ln\left(\mathcal{D}\frac{\Pi_2 - 1}{1 - \frac{1}{\Pi_1}}\right)$$

[26] $\frac{c_t^1}{c_t^u}$ is constant since $c_t^u = c_t^{s2}$, $\frac{c_t^1 - c_t^{s1}}{1-s} = w_t^1$, $\frac{c_t^2 - c_t^{s2}}{1-s} = w_t^2$ and $\frac{w_t^1}{w_t^2} = \mathcal{D}$ implies $\frac{c_t^1}{c_t^{s2}} = \mathcal{D}\frac{\Pi_2 - 1}{1 - \frac{1}{\Pi_1}}$.

As a result, if $\theta_t^1 = \omega\theta_t^2$ for all t, $x_t^1 = x^1$ and $x_t^2 = 1 - x_t^1 = 1 - x^1 = x^2$. However, if $\frac{\theta_t^2}{\theta_t^1}$ increases, $\frac{N_t^2}{N_t^1}$ increases, which causes x_t^1 to decrease and x_t^2 to increase. Therefore, as jobs increase in one sector relative to another, more people will look for work in the growing sector.

3.7. Queues

Next, I present the model's predictions about queue size since past work has suggested that if wages are high due to efficiency wage considerations, there should be larger queues for jobs in these high paying industries/firms.[27] Here, the queue size is defined by the ratio of the number of workers willing to accept employment in that industry to the number of jobs available in the industry to give a measure of applicants per job.

In the first case discussed above, individuals can search for work in both sectors simultaneously. Here, since all workers would accept employment in the high wage industry, while only workers without job offers from the high wage industry would accept employment in the low wage industry, it follows that the total number of applications in the high wage industry exceeds the number in the low wage industry, $x_t^1 > x_t^2$. However, whether the queue for a job is larger in the high wage industry than in the low wage industry, $\left(\text{i.e., whether } \frac{x_t^1}{N_t^1} > \frac{x_t^2}{N_t^2}\right)$, will depend on the relative size of the number of jobs available in each industry. For example, if $N_t^1 < N_t^2$, as it generally is in the data, then clearly $\frac{x_t^1}{N_t^1} > \frac{x_t^2}{N_t^2}$, but if the number of jobs in the high wage industry was much larger than the number of jobs in the low wage industry, then $\frac{x_t^1}{N_t^1} < \frac{x_t^2}{N_t^2}$. Consequently, the model's prediction for queue size is dependent on the values of its parameter.

[27] See e.g., Weiss (1990).

Although it is not possible to prove that the size of the queue is always greater in the high wage industry when workers are able to search for jobs in both industries simultaneously, it is possible to prove that $\frac{x_t^1}{N_t^1} > \frac{x_t^2}{N_t^2}$ if workers are only able to search in one industry at a time. In particular, since wages are higher and effort is lower in the low detection industry, $f_0 > f_1$.Therefore, if workers only search in one sector of the economy at a time, the model predicts that queues will always be larger in the high wage industry since:

$$\frac{x_t^1}{N_t^1} - \frac{x_t^2}{N_t^2} > 0 \iff \frac{x_t^1}{N_t^1}\frac{N_t^2}{x_t^2} > 1 \iff \frac{N_t^2}{N_t^1}\left(\frac{f_0}{f_1\frac{N_t^2}{N_t^1}}\right) > 1 \iff f_0 > f_1$$

3.8. Unmeasured Ability

An alternate theory of inter-industry wage differentials proposes that workers with the same measurable attributes receive different wages because there are systematic differences in unmeasured worker ability that are correlated with industry affiliation.[28] Therefore, it is important to investigate how the addition of ability affects the results of the model.

To determine the consequences of adding workers with different ability, I consider a simple case where there are only two types of workers in the economy, and explore the properties of the model for the equilibrium where the high ability individuals are employed in the high paying industry. Type 1 agents are assumed to have higher ability than type 2 agents in Industry 1 (the high wage industry), and the same ability as type 2 workers in Industry 2. In contrast, type 2 agents have the same ability in both industries. Furthermore, I assume that there are a large number of agents of both types (so there is no shortage of either type of worker) and I analyze two ways of incorporating ability into the model.

In the first case, I assume that the worker's ability affects the amount of effective labor

[28] For example, Murphy and Topel (1987) argue that unmeasured worker ability, not efficiency wage considerations, are responsible for the majority of the wage differentials seen in the data.

that is provided to firms. In particular, if a_i^j is the level of individual $i's$ ability in industry j, then for a given level of effort in industry j, e_i^j, this individual contributes $a_i^j e_i^j$ units of effective labor to his firm. As a result, firms in industry j now have the following production function:

$$Y_t^j = \theta_t^j \left(K_t^j\right)^\alpha (N_{1t}^j a_1^j e_{1t}^j + N_{2t}^j a_2^j e_{2t}^j)^{1-\alpha}$$

where N_{it}^j is the number of workers of type i hired by the firm in industry j. In addition, when the firms maximize profits, they faces the same incentive compatibility constraints as before because a worker's ability does not directly enter into his utility function.

It is straight forward to demonstrate that when there is no shortage of workers, firms in industry 1 will choose to hire only one type of worker in equilibrium while firms in industry 2 will hire either type of worker.[29] In the sorting equilibrium, where type 1 workers are hired in industry 1, the high ability of the type 1 individuals acts as an increase in the level of technology used in industry 1 and causes more type 1 workers to be hired into that industry. However, wages and effort levels will still be determined by the Solow condition. Therefore, although the model is consistent with the empirical observation that high ability individuals are generally found in the high wage sector, the inter-industry wage differential remains as it was before, $\left(\text{i.e., } \frac{w_t^1}{w_t^2} = \frac{(1-s\Pi_2)(\Pi_1-1)}{(1-s\Pi_1)(\Pi_2-1)} = \mathcal{D}\right)$. The value of the differential in this case is not dependant on the ability of workers hired - it is solely determined by the parameter values ξ, s, $\frac{d_1}{\gamma}$, $\frac{d_2}{\gamma}$, and T.

In the second case, I assume that an individual's ability affects his utility from working by altering the fixed cost associated with working. Specifically, individuals with higher ability

[29] This occurs since type 1 individuals have higher ability in industry 1, so that for a given level of effort, $a_1^1 e > a_2^1 e$.

will have lower costs associated with providing effort on the job so that:

$$\xi_i^1 = \xi - h(a_i^1)$$
$$\xi_i^2 = \xi$$

where $h(\cdot) > 0$, and $h'(\cdot) > 0$ for all i. Therefore, type 1 workers incur lower fixed costs in industry 1 than type 2 workers, while the fixed cost is independent of type in industry 2.

Firms in industry j face the following problem when there is no shortage of workers:

$$\max_{\left\{K_t^j, N_{1t}^j, w_{1t}^j,, N_{2t}^j, w_{2t}^j, P_t^j\right\}} P_t^j Y_t^j - r_t^j K_t^j - w_{1t}^j N_{1t}^j - w_{2t}^j N_{2t}^j$$

subject to:

$$Y_t^j = \theta_t^j (K_t^j)^{\alpha} (N_{1t}^j e_{1t}^j + N_{2t}^j e_{2t}^j)^{1-\alpha}$$
$$e_{it}^j = T\left(1 - \left(\frac{c_{it}^j}{c_{it}^{sj}}\right)^{-\frac{d_j}{\gamma}}\right) - \xi_i^j \text{ for } i = 1, 2$$
$$Y_t^j = Y_t(\overline{P}_t^j)^{\frac{\mu-\phi}{(\mu-1)(\phi-1)}} P_t^{j\,\frac{-\phi}{\phi-1}}$$

where N_{it}^j is the number of workers of type i hired by the firm in industry j, e_{it}^j is the effort required from a worker of type i working for a firm in industry j, ξ_i^j is type $i's$ fixed cost of providing effort in industry j, c_{it}^j is the consumption enjoyed by a type i worker who is not detected shirking, and c_{it}^{sj} is the consumption enjoyed by a type i worker who is detected shirking. Again it is straight forward to show that the firms in industry 1 will only hire one type of worker, while firms in industry 2 are again indifferent between the different types.

In the sorting equilibrium, where type 1 workers are hired by firms in industry 1, type 1 workers employed in industry 1 receive lower wages than type 2 workers would be paid if they were hired in industry 1. This result follows from the assumption that high ability workers have a lower fixed cost of providing effort in this industry. Firms know that it is not as difficult to induce high ability types to provide effort as low ability types because of the difference in their fixed costs. Therefore, the high ability workers will not require as high a wage as low ability workers for a given level of effort in industry 1. Since ability puts downward pressure on wages in this case, it makes it harder, not easier, to explain sizable inter-industry wage differentials. In particular, as the fixed cost of providing effort decreases for the high ability workers in industry 1, Π_1 decreases, which causes $\frac{w_t^1}{w_t^2} = \frac{(1-s\Pi_2)(\Pi_1-1)}{(1-s\Pi_1)(\Pi_2-1)}$ to fall.

The two methods of modelling unobserved ability examined suggest that, even though differences in ability has been proposed as a major determinant of inter-industry wage differentials, the presence of workers with different abilities may not help explain the inter-industry wage differentials when firms only imperfectly observe worker effort. However, the theoretical results may help explain Gibbons and Katz's (1992) empirical findings that while workers' traits affect mobility, the direct effect of these traits on wages are small or nonexistent.

4. AN EMPIRICAL ANALYSIS

While it is promising that the model is capable of reproducing a number of stylized facts, it remains important to: (1) determine how large the differences in detection rates must be in order to obtain the sizable differentials seen in the data and (2) examine how wages and employment respond to technology shocks. If the model fails to deliver either sizable inter-industry differentials with small differences in d or high employment volatility alongside low real wage volatility, this will cast some doubt on the shirking efficiency wage theory of inter-industry wage differentials.

4.1. Estimating the Inter-Industry Wage Differentials

Although previous studies, such as Krueger and Summers (1988), report that the inter-industry wage differentials are highly persistent over time, little information exists regarding how inter-industry wage differentials behave over the business cycle. This additional information, along with the magnitude of the estimated differentials, will help calibrate the parameters of the model and test whether a multi-sector model's predictions are consistent with the empirical evidence.[30]

In this section, I repeat the analysis conducted by Krueger and Summers (1988) using data from the yearly May Current Population Surveys over the period 1973 to 1999.[31] The May supplement is chosen for two reasons. First, it contains pertinent information about labor force participants who are 14 years of age or older. Second, only the May survey contains information on weekly earnings in the earlier years of the sample.

The sample contains full and part-time non-agricultural workers, who are at least 16 years of age and who report usually earning between \$1.00 and \$250.00 an hour.[32] Next, to establish the importance of industry affiliation in determining usual hourly earnings, the log hourly wage is regressed on the one-digit census dummy variables, and human capital

[30] Keane (1993) finds that inter-industry wage differentials are acyclical over the period 1966-81 and argues that this is inconsistent with efficiency wage theories of the differentials.

[31] Although it would be useful to have data over a longer period of time, there have been significant changes in the occupation and industry codes and the way that usual earnings and hours are reported that limit the time over which meaningful comparisons can be made between estimates.

[32] Usual hourly earnings are defined as usual weekly earnings divided by usual weekly hours. The upper bound reflects topcoding in the data as well as an assumption made about feasible earnings for the categories of workers we examine. For example, a full time employee at 40 hours a week who earned \$250 an hour could earn as much as \$520,000. Therefore, eliminating people above this level will simply remove some of the outliers in the sample.

and demographic controls. As in Krueger and Summers (1988), the human capital and demographic controls consist of 9 occupation variables, a measure of education, an age variable, sex, race, union status, veteran status, a central city dummy variable, marital status, and a number of interaction terms.[33] Specifically, the yearly estimates of the inter-industry wage differentials are obtained by estimating the wage equation:

$$\ln(w) = \alpha + \beta X + D\gamma + \Omega O + \varepsilon$$

where w is the hourly wage of an individual, γ is a vector of mutually exclusive industry dummy variables, X is a vector of individual characteristics and locational variables, and O is a vector of mutually exclusive occupation dummy variables.[34] Finally, to facilitate a comparison between the yearly estimates, the definitions of the variables used in the regressions are kept as consistent as possible over the years.[35]

The inter-industry differentials, $\mathfrak{D}$, reported in Table 1, are differences between the industry differentials and the employment weighted average of D.[36] Therefore, the resulting statistics correspond to the percentage increase (or decrease) in wages between an average

[33] The interaction terms include: (age)X(sex), (martial status)X(sex), (education)X(sex) and (education^2)X(sex). The union variable was unavailable in 1982. However, sensitivity analysis suggests that the results do not critically depend on this variable.

[34] Since the regression includes a constant, the omitted industry variable, (i.e., mining), is treated as having a zero effect on wages, following Krueger and Summers' (1988) methodology.

[35] There are a number of changes in the available data over the sample period. One example of such a change is found in the way the worker's education is reported. Prior to 1991, the CPS gives a measure of education based on the number of years of schooling that the individual has completed. From 1991 onwards, the CPS only collected information on whether an individual completed a high-school degree, college degree, etc. Since the pre and post 1991 measures are not directly comparable, I use the procedure suggested in Jaeger (1997) to define an education measure that is more consistent across the time period in question.

[36] Following Krueger and Summers (1987), the differentials are computed as follows:

$$\mathfrak{D}_j = D_j - \sum_{j=0}^{6} s_j D_j = D_j - \sum_{j=1}^{6} s_j D_j$$

where s_j is the share of employment in industry j, and $D_0 = 0$ for mining.

worker in the specific industry and the average wage of a worker in all industries after controlling for demographic and human capital variables. Figure 1 graphs the estimated values of $\mathfrak{D}$ and the unemployment rate to illustrate size of the differentials across industries and their behavior over the business cycle. The findings suggest that the mining industry generally pays workers the highest wages, the service industry always has the second lowest wages and the wholesale and retail trade (TRADE) industry consistently has the lowest wages. However, the rankings of the manufacturing industry (MANUF), the construction industry (CONSTR), the transportation industry (TRANSP) and the finance, insurance and real estate industry (FINANCE), are not as clear. This is apparent in Table 2, where the average value of the differentials, as well as the average rank of the differential for each industry, are reported.[37] These statistics suggest that workers in the construction and transportation industries generally have higher wages than workers in either the finance, insurance, and real estate industry or the manufacturing industry. However, no conclusive statement can be made concerning ranking wages in the transportation industry versus wages in the construction industry, or wages in the finance, insurance and real estate industry versus the wages in the manufacturing industry.

Although it appears from Figure 1 that the differentials are not cyclical over the time period, it is useful to check this formally by running the following regression:

$$\Delta\widehat{\mathfrak{D}}_t^i = \alpha + \beta\Delta u_t + \gamma t + v_t$$

where v_t is white noise, t is a time trend, and $\Delta\widehat{\mathfrak{D}}_t^i$ and Δu_t are the first differences of the

[37] Each year the industries were assigned a value that corresponded to their ranking, (i.e., the industry with the highest wage differential was assigned a value of 1, the industry with the second highest received the value 2, etc.). The average rank of the differentials reported represent the average of the industries' yearly rank values.

estimated interindustry wage differentials and the unemployment rate respectively.[38] The results of this regression are found in Table 3. The results support the hypothesis that there is no significant cyclicality in the inter-industry wage differentials. This finding is consistent with Keane's (1993) findings using the National Longitudinal Survey of Young Men for the time period 1966-1981.

4.2. A Calibrated Model with 7 Industries

To analyze whether the model can replicate the empirical findings, and to determine if small differences in the rates of detection across industries can produce sizable inter-industry wage differentials, a version of the model with 7 industries is calibrated. The calibration exercise is discussed below.

In the model, the percentage difference between the wage in industry i, i=1,..7, and the average wage when there are 7 industries in the economy is:

$$\begin{aligned}\frac{w^i}{\overline{w}} &= \frac{w^i}{\left(\sum_{i=1}^{7} w^i N^i\right) / \left(\sum_{i=1}^{7} N^i\right)} = \frac{w^i \left(\sum_{i=1}^{7} N^i\right)}{\left(\sum_{i=1}^{7} w^i N^i\right)} \\ &= \frac{w^7 \mathcal{D}^i N^7 \left(\sum_{i=1}^{7} \frac{N^i}{N^7}\right)}{w^7 N^7 \left(\sum_{i=1}^{7} \left(\mathcal{D}^i \frac{N^i}{N^7}\right)\right)} = \frac{\mathcal{D}^i \left(\sum_{i=1}^{7} \frac{N^i}{N^7}\right)}{\left(\sum_{i=1}^{7} \left(\mathcal{D}^i \frac{N^i}{N^7}\right)\right)}\end{aligned}$$

where $\mathcal{D}^i$ is the constant differential, $\frac{w^i}{w^7}$, implied by the model when w^7 is the wage in the industry with the highest rate of detection, (i.e., the lowest wage). Since the differentials $\{\mathcal{D}^1, \mathcal{D}^2, ..., \mathcal{D}^7\}$ are independent of the time period and state of the world, the behavior of $\frac{w^i}{\overline{w}}$ depends on the behavior of $\frac{N^i}{N^7}$. From the results in Section 3, it is clear that $\frac{w^i}{\overline{w}}$ is acyclical whenever the technology levels in the different industries are directly proportional to one another. Therefore, given the acyclicality of the estimated inter-industry wage differentials,

[38] To coincide with the timing of the CPS data, the unemployment rate used is the yearly average from May to May.

the model is calibrated under the assumption that $\theta^i = \omega_i \theta^7$. Furthermore, it is assumed that the technology level in industry i is determined by the equation:

$$\left(\theta_{t+1}^i - \theta^{iss}\right) = \rho_\theta \left(\theta_t^i - \theta^{iss}\right) + \varepsilon_t$$

where θ^{iss} is the steady state level of the technology in industry i, $0 < \rho_\theta < 1$ and ε is a mean zero i.i.d. shock.

The remaining parameter values are calibrated according to the following criteria. First, the aggregate unemployment rate in the model is approximately 6.0%. Second, the percentage of individuals employed in each industry in the model is equal to the average employment shares seen in the CPS data.[39] Third, the wage differentials in the model equal the average differentials estimated from the data, and fourth, the values for α, β, δ, T, and the markups are consistent with values seen in the real business cycle literature.[40] This calibration strategy yields the following parameter values:

ω_1	ω_2	ω_3	ω_4	ω_5	ω_6	ω_7	ρ_θ	β	α	$\mu = \phi$	δ
0.85	1.13	1.10	1.06	1.37	1.14	1.00	0.9	$\left(\frac{1}{1.03}\right)^{.25}$	0.34	1.2	0.025

$\frac{d_1}{\gamma}$	$\frac{d_2}{\gamma}$	$\frac{d_3}{\gamma}$	$\frac{d_4}{\gamma}$	$\frac{d_5}{\gamma}$	$\frac{d_6}{\gamma}$	$\frac{d_7}{\gamma}$	T	ξ	s
0.4795	0.4950	0.4950	0.5052	0.5045	0.5382	0.5625	1369	0.95	0.95

and produces the steady state employment shares and wage differentials reported in Tables 4 and 5. These results indicate that small differences between the industries' probability of

[39] Here I assume that industry 1 is assumed to be the industry with the highest wage in the data (i.e., mining) and industry 7 is the industry with the lowest wage (i.e., trade). For industries 2 to 6, the employment shares in the model are matched to the industry data for the industry with the same rank based on average size of the wage differential.

[40] See e.g., Burnside and Eichenbaum (1996), and Alexopoulos (2004).

detecting shirkers, $\left(\text{i.e., } \left|\frac{d_1 - d_7}{d_7}\right| \times 100\% \simeq 17\%\right)$, can reproduce the substantial differences in wages across industries.[41]

Since there is debate over how much of the inter-industry wage differentials are due to efficiency wage considerations, I also examine what values of d_i would be necessary to explain 1/3 of the estimated differentials (i.e., the estimate of the unexplained portion of inter-industry wage differentials suggested by Murphy and Topel (1987)). In this case, simulations of the model suggest that only a difference in detection rates of less than 5% between the highest and lowest paid industries would be required. Consequently, the model indicates that even though studies like Walsh (1999) have not found large cross-industry differences in the detection rates using noisy proxies such as supervisors per worker, their findings should not be viewed as conclusive evidence against the efficiency wage theory of inter-industry wage differentials.

4.3. The Response to an Aggregate Technology Shock

As mentioned above, the multi-sector model must also be able to generate small real wage movements alongside large employment changes in order to be consistent with the data. Figure 2 demonstrates that the model is capable of reproducing these regularities. In response to a 1% unexpected increase in technology, the model generates a modest increase in real wages alongside a large gain in employment (see Figure 2).[42] Specifically, the model

[41] To change this computation into levels, a value of γ must be chosen. For example, when $\gamma = 1.75$, the difference between the detection rates in the highest and lowest paid industries would be approximately 14%.

[42] The model's responses to technology shocks are virtually identical to those presented in Alexopoulos (2004) for two reasons. First, Y_t in the multi-sector model can be rewritten as $Y_t = \widetilde{\theta}_t (K_t)^{\alpha} (eN_t)^{1-\alpha}$, where K_t and eN_t are the aggregate capital levels and effective labor input respectively $\widetilde{\theta}_t$ is the aggregate level of technology. Second, the only significant difference between the basic set-up of the environments is that here I allow $\mu > 1$ so that firms can choose prices.

suggests that, for these parameter values, the percent deviation of employment from its steady state value in response to a technology shock is at least two times larger than the response of real wages.

These results also hold at the industry level. Given that the calibrated model implies that $K_t^i \propto K_t^7, N_t^i \propto N_t^7, e_t^i = e^i, \theta_t^i = \omega^i \theta_t^7, w_t^i \propto w_t^7, Y_t^i \propto Y_t^7 \; \forall i$, is it straight forward to demonstrate that aggregate levels of output, Y_t, investment, I_t, consumption, C_t, employment, N_t, unemployment, U_t and real wages W_t, also vary proportionately with the industry level values of the same variables.[43] Therefore, the industry level responses to a positive technology shock are identical to the aggregate responses reported in Figure 2.

5. CONCLUSIONS

The paper presents a multi-industry shirking efficiency wage model where: (i) detected shirkers are assumed to forgo a portion of their compensation, and (ii) the firms' ability to detect shirking workers varies across sectors. A number of interesting results emerge from this analysis. First, the model with monetary punishments is able to reproduce the stability of the inter-industry wage differentials observed in the U.S. economy. Second, with only small differences in the probability of detection across industries, the model can generate inter-industry wage differentials that are similar in magnitude to those estimated from the data. Third, the model is consistent with the empirical evidence that indicates high wage industries tend to have higher capital-to-labor ratios, larger profits per worker and longer

[43] For example, for the case with 7 industries $Y_t = Y_t^7 \left(\sum_{i=1}^7 \left(\frac{Y_t^i}{Y_t^7} \right)^{\frac{1}{\mu}} \right)^{\mu} = Y_t^7 \left(\sum_{i=1}^7 \left(\frac{\theta_t^i}{\theta_t^7} \left(\frac{K_t^i}{K_t^7} \right)^{\alpha} \left(\frac{e^i N_t^i}{e^7 N_t^7} \right)^{1-\alpha} \right)^{\frac{1}{\mu}} \right)^{\mu}$. However, given that $\theta_t^i = \omega^i \theta_t^7$ and the results derived in the propositions generalize to this case, the equation can be rewritten as $Y_t = Y_t^7 \Psi$, where Ψ is a constant.

job queues. Fourth, the theoretical results suggest that differences in worker ability may not help explain large inter-industry wage differentials when firms cannot perfectly monitor workers' effort levels. Finally, the calibrated model is consistent with the acyclicality of my estimated inter-industry wage differentials as well as the observation that real wages are only mildly procyclical while employment is strongly procyclical over the business cycle.

In aggregate, the work in this paper provides additional support for the theory that shirking efficiency wage frictions can help explain a significant part of inter-industry wage differentials, as well as other labor market phenomena, such as the presence of unemployment and the observed behavior of wages and employment over the business cycle. Although the paper does not rule out other potential explanations of inter-industry wage differentials, it does illustrate that differences in worker ability may not help explain the differentials when firms face problems detecting shirking workers. As a result, future work should concentrate on designing alternative tests to clarify the importance of these efficiency wage considerations in determining wages and inter-industry wage differentials.

APPENDIX A: Proofs of Propositions

Proof of Proposition 1

Let $\Pi_j = \frac{c_t^j}{c_t^{sj}}$. Then the value of Π_j is determined by the Solow condition

$$0 = T\frac{d_j}{\gamma}(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{(1-s\Pi_j)}{1-s}(\Pi_j-1) - T\left(1-(\Pi_j)^{-\frac{d_j}{\gamma}}\right) + \xi \equiv H$$

Notice that this equation, and the condition that effort is positive, implies that $\Pi_j \in (1, \frac{1}{s})$.

Next use the implicit function theorem to get $\frac{\partial \Pi_j}{\partial \frac{d_j}{\gamma}}$.

$$\begin{aligned}
H_{\Pi_j} &= T\frac{d_j}{\gamma}\left[-\left(\frac{d_j}{\gamma}+1\right)\right](\Pi_j)^{-\frac{d_j}{\gamma}-2}\frac{(1-s\Pi_j)}{1-s}(\Pi_j-1) - T\frac{d_j}{\gamma}(\Pi_j)^{-\frac{d_j}{\gamma}-1} \\
&\quad -T\frac{d_j}{\gamma}(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{s}{1-s}(\Pi_j-1) + T\frac{d_j}{\gamma}(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{(1-s\Pi_j)}{1-s} \\
&= T\frac{d_j}{\gamma}\left[-\left(\frac{d_j}{\gamma}+1\right)\right](\Pi_j)^{-\frac{d_j}{\gamma}-2}\frac{(1-s\Pi_j)}{1-s}(\Pi_j-1) \\
&\quad +T\frac{d_j}{\gamma}(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{1}{1-s}\left\{-s(\Pi_j-1)+1-s\Pi_j-(1-s)\right\} \\
&= T\frac{d_j}{\gamma}\left[-\left(\frac{d_j}{\gamma}+1\right)\right](\Pi_j)^{-\frac{d_j}{\gamma}-2}\frac{(1-s\Pi_j)}{1-s}(\Pi_j-1) \\
&\quad +T\frac{d_j}{\gamma}(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{1}{1-s}\left\{-s\Pi_j+s+1-s\Pi_j-1+s)\right\} \\
&= T\frac{d_j}{\gamma}\left[-\left(\frac{d_j}{\gamma}+1\right)\right](\Pi_j)^{-\frac{d_j}{\gamma}-2}\frac{(1-s\Pi_j)}{1-s}(\Pi_j-1) + T\frac{d_j}{\gamma}(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{1}{1-s}\left\{2s(1-\Pi_j)\right\}
\end{aligned}$$

Therefore, $H_{\Pi_j} < 0$ since $\Pi_j > 1$. Next, the sign of $H_{\frac{d_j}{\gamma}}$ needs to be determined.

$$H_{\frac{d_j}{\gamma}} = T(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{(1-s\Pi_j)}{1-s}(\Pi_j-1) - T\frac{d_j}{\gamma}(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{(1-s\Pi_j)}{1-s}(\Pi_j-1)\ln(\Pi_j) - \ln(\Pi_j)T(\Pi_j)^{-\frac{d_j}{\gamma}}$$

Remembering that the definition of H implies that

$$-\ln(\Pi_j)T(\Pi_j)^{-\frac{d_j}{\gamma}} = \ln(\Pi_j)\left[T\frac{d_j}{\gamma}(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{(1-s\Pi_j)}{1-s}(\Pi_j-1) - T + \xi\right]$$

and substituting this expression into the previous equation produces the expression:

$$
\begin{aligned}
H_{\frac{d_j}{\gamma}} &= T(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{(1-s\Pi_j)}{1-s}(\Pi_j-1)\left[1-\ln(\Pi_j)\frac{d_j}{\gamma}+\ln(\Pi_j)\frac{d_j}{\gamma}\right]-\ln(\Pi_j)\left[T-\xi\right] \\
&= T(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{(1-s\Pi_j)}{1-s}(\Pi_j-1)-\ln(\Pi_j)\left[T-\xi\right] \\
&= \frac{T\left(1-(\Pi_j)^{-\frac{d_j}{\gamma}}\right)-\xi}{\frac{d_j}{\gamma}}-\ln(\Pi_j)\left[T-\xi\right] \text{ (also from the definition of H)}
\end{aligned}
$$

Clearly if Π_j is close to 1, $H_{\frac{d_j}{\gamma}} < 0$. However, this is more clearly shown by defining a function $J(\Pi_j)$, where

$$
J(\Pi_j) = \frac{T\left(1-(\Pi_j)^{-\frac{d_j}{\gamma}}\right)-\xi}{\frac{d_j}{\gamma}}-\ln(\Pi_j)\left[T-\xi\right]
$$

$J(\Pi_j)$ is a strictly decreasing function when $\Pi_j \in (1, \frac{1}{s})$. i.e.

$$
\begin{aligned}
J'(\Pi_j) &= T(\Pi_j)^{-\frac{d_j}{\gamma}-1}-\frac{T-\xi}{\Pi_j} = \frac{1}{\Pi_j}\left[-(T-\xi)+T\Pi_j^{-\frac{d_j}{\gamma}}\right] \\
&= \frac{1}{\Pi_j}\left[-(T-\xi)-T\frac{d_j}{\gamma}(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{(1-s\Pi_j)}{1-s}(\Pi_j-1)+(T-\xi)\right] \text{ (From H=0)} \\
&= \frac{1}{\Pi_j}\left[-T\frac{d_j}{\gamma}(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{(1-s\Pi_j)}{1-s}(\Pi_j-1)\right] < 0
\end{aligned}
$$

It then follows that $H_{\frac{d_j}{\gamma}} < \max J(\Pi_j) = J(1) < 0$. As a result, the Implicit Function Theorem implies that $\frac{\partial \Pi_j}{\partial \frac{d_j}{\gamma}} = -\frac{H_{\frac{d_j}{\gamma}}}{H_{\Pi_j}} < 0$, and since d_j only appears in the equations in the ratio $\frac{d_j}{\gamma}$, it follows that

$$
\frac{\partial \Pi_j}{\partial d_j} = \frac{\partial \Pi_j}{\partial \frac{d_j}{\gamma}}\frac{\partial \frac{d_j}{\gamma}}{\partial d_j} = \frac{\partial \Pi_j}{\partial \frac{d_j}{\gamma}}\frac{1}{\gamma} < 0
$$

Proof of Proposition 2

$\frac{w_t^1}{w_t^2} = \mathcal{D} = \frac{(1-s\Pi_2)(\Pi_1-1)}{(1-s\Pi_1)(\Pi_2-1)}$. Also we know that $d_1 < d_2$ implies that $\Pi_1 > \Pi_2$ according to the previous proposition. To prove that $\mathcal{D} > 1$, examine the function $M(z) = \frac{z-1}{1-sz}$. Notice $M'(z) = \frac{1-s}{(1-sz)^2} > 0$. Therefore $\Pi_1 > \Pi_2 \Rightarrow H(\Pi_1) > H(\Pi_2) \Rightarrow \mathcal{D} = \frac{H(\Pi_1)}{H(\Pi_2)} > 1$

Proof of Proposition 3

$$\frac{\partial e^i}{\partial \frac{d_j}{\gamma}} = T\ln(\Pi_j)(\Pi_j)^{-\frac{d_j}{\gamma}} + T\frac{d_j}{\gamma}(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{\partial \Pi_j}{\partial \frac{d_j}{\gamma}} = T(\Pi_j)^{-\frac{d_j}{\gamma}-1}\left[\Pi_j \ln(\Pi_j) + \frac{d_j}{\gamma}\frac{\partial \Pi_j}{\partial \frac{d_j}{\gamma}}\right]$$

To sign $\left[\Pi_j \ln(\Pi_j) + \frac{d_j}{\gamma}\frac{\partial \Pi_j}{\partial \frac{d_j}{\gamma}}\right]$ it is useful to break the expression into parts. First

$$\begin{aligned}
\frac{d_j}{\gamma}\frac{\partial \Pi_j}{\partial \frac{d_j}{\gamma}} &= -\frac{d_j}{\gamma}\frac{T(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{1}{1-s}\left\{(1-s\Pi_j)(\Pi_j-1)\left(1-\frac{d_j}{\gamma}\ln(\Pi_j)\right)-\Pi_j\ln(\Pi_j)(1-s)\right\}}{T(\Pi_j)^{-\frac{d_j}{\gamma}-1}\frac{1}{1-s}\frac{d_j}{\gamma}\left\{\frac{-\left(\frac{d_j}{\gamma}+1\right)}{\Pi_j}(1-s\Pi_j)(\Pi_j-1)+2s(1-\Pi_j)\right\}} \\
&= \frac{-\left\{(1-s\Pi_j)(\Pi_j-1)\left(1-\frac{d_j}{\gamma}\ln(\Pi_j)\right)-\Pi_j\ln(\Pi_j)(1-s)\right\}}{\left\{\frac{-\left(\frac{d_j}{\gamma}+1\right)}{\Pi_j}(1-s\Pi_j)(\Pi_j-1)+2s(1-\Pi_j)\right\}} \equiv \frac{A}{B}
\end{aligned}$$

Then let $C \equiv B\Pi_j \ln(\Pi_j)$. In this case, the sign of $\frac{\partial e^i}{\partial \frac{d_j}{\gamma}}$ is determined by the sign of $\frac{A+C}{B}$. Since $\Pi_j \in (1, \frac{1}{s})$, $B < 0$. Therefore, the sign of $\frac{\partial e^i}{\partial \frac{d_j}{\gamma}}$ is determined by the sign of $A + C$.

$$\begin{aligned}
A+C &= -(1-s\Pi_j)(\Pi_j-1)\left(1-\frac{d_j}{\gamma}\ln(\Pi_j)\right)+\Pi_j\ln(\Pi_j)(1-s) \\
&\quad +\Pi_j\ln(\Pi_j)\left\{\frac{-\left(\frac{d_j}{\gamma}+1\right)}{\Pi_j}(1-s\Pi_j)(\Pi_j-1)+2s(1-\Pi_j)\right\} \\
&= -(1-s\Pi_j)(\Pi_j-1)\left(1-\frac{d_j}{\gamma}\ln(\Pi_j)\right)+\Pi_j\ln(\Pi_j)(1-s) \\
&\quad +\ln(\Pi_j)\left\{-\left(\frac{d_j}{\gamma}+1\right)(1-s\Pi_j)(\Pi_j-1)+2s\Pi_j(1-\Pi_j)\right\} \\
&= -(1-s\Pi_j)(\Pi_j-1)(1-\frac{d_j}{\gamma}\ln(\Pi_j))+\Pi_j\ln(\Pi_j)(1-s) \\
&\quad -\left(\frac{d_j}{\gamma}+1\right)(1-s\Pi_j)(\Pi_j-1)\ln(\Pi_j)-\ln(\Pi_j)2s\Pi_j(\Pi_j-1) \\
&= -(1-s\Pi_j)(\Pi_j-1)\left[1-\frac{d_j}{\gamma}\ln(\Pi_j)+\left(\frac{d_j}{\gamma}+1\right)\ln(\Pi_j)\right]+\Pi_j\ln(\Pi_j)\left[(1-s)-2s\Pi_j+2s\right] \\
&= -(1-s\Pi_j)(\Pi_j-1)\left[1+\ln(\Pi_j)\right]+\Pi_j\ln(\Pi_j)\left[(1+s-2s\Pi_j\right] \\
&= -\ln(\Pi_j)\left[(1-s\Pi_j)(\Pi_j-1)-\Pi_j(1-s\Pi_j)+\Pi_j s(\Pi_j-1)\right]-(1-s\Pi_j)(\Pi_j-1)
\end{aligned}$$

$$
\begin{aligned}
&= -\ln(\Pi_j)\left[(1-s\Pi_j)\Pi_j - (1-s\Pi_j) - \Pi_j(1-s\Pi_j) + \Pi_j s(\Pi_j-1)\right] - (1-s\Pi_j)(\Pi_j-1) \\
&= -\ln(\Pi_j)\left[-1 + s\Pi_j - \Pi_j s + s(\Pi_j)^2\right] - (1-s\Pi_j)(\Pi_j-1) \\
&= -\ln(\Pi_j)\left[s(\Pi_j)^2 - 1\right] - (1-s\Pi_j)(\Pi_j-1)
\end{aligned}
$$

If $[s(\Pi_j)^2 - 1] > 0$, then clearly $A + C < 0$. However, it is necessary to consider the case where $[s(\Pi_j)^2 - 1] < 0$ and $\Pi_j \in (1, \frac{1}{s})$.Note that $\Pi_j > 1 \Leftrightarrow (\Pi_j)^2 > \Pi_j \Leftrightarrow -s(\Pi_j)^2 < -s\Pi_j \Leftrightarrow 1 - s(\Pi_j)^2 < 1 - s\Pi_j \Leftrightarrow \ln(\Pi_j)(1 - s(\Pi_j)^2) < \ln(\Pi_j)(1 - s\Pi_j)$. Therefore, under these conditions,

$$
\begin{aligned}
A + C &= \ln(\Pi_j)\left[1 - s(\Pi_j)^2\right] - (1-s\Pi_j)(\Pi_j-1) \\
&< \ln(\Pi_j)\left[1 - s\Pi_j\right] - (1-s\Pi_j)(\Pi_j-1) = -(1-s\Pi_j)\left[\Pi_j - 1 - \ln(\Pi_j)\right]
\end{aligned}
$$

Let $W(\Pi_j) \equiv \Pi_j - 1 - \ln(\Pi_j)$. Then $W'(\Pi_j) = 1 - \frac{1}{\Pi_j} > 0$ for $\Pi_j \in (1, \frac{1}{s})$, and $W(1) = 0$. As a result, $W(\Pi_j) > W(1) = 0$ for $\Pi_j \in (1, \frac{1}{s})$. Therefore, $A + C < 0$ if $[s(\Pi_j)^2 - 1] < 0$. More importantly, since all cases imply that $A + C < 0$, $\frac{A+C}{B} > 0 \Rightarrow \frac{\partial e^i}{\partial \frac{d_j}{\gamma}} > 0$. Since d_j only appears in the equations in the ratio $\frac{d_j}{\gamma}$, it follows that

$$
\frac{\partial e^i}{\partial d_j} = \frac{\partial e^i}{\partial \frac{d_j}{\gamma}} \frac{\partial \frac{d_j}{\gamma}}{\partial d_j} = \frac{\partial e^i}{\partial \frac{d_j}{\gamma}} \frac{1}{\gamma} > 0
$$

Therefore, $d_1 < d_2 \Rightarrow e^1 < e^2$.

Proof of Proposition 4

Here the variables without time subscripts denote the steady state levels of the variables.

$$
\frac{\partial N_1}{\partial \frac{d_1}{\gamma}} = \frac{\partial \left[\frac{(1-\alpha)(1-s)r}{\left[(1-\alpha)rs\left(\mathcal{D}y^{\frac{1}{\mu}}+1\right)+\alpha\left(\mathcal{D}y^{\frac{1}{\mu}}+\mathcal{D}\right)\left(r^{\frac{\mu-1+\alpha}{\alpha}}-\delta\right)\right](\Pi_2-1)} \right]}{\partial \frac{d_1}{\gamma}}
$$

$$
= \frac{-(1-\alpha)(1-s)r\left[\left((1-\alpha)rs + \alpha\left(r^{\frac{\mu-1+\alpha}{\alpha}} - \delta\right)\right)\frac{\partial \mathcal{D}y^{\frac{1}{\mu}}}{\partial \frac{d_1}{\gamma}} + \frac{\partial \mathcal{D}}{\partial \frac{d_1}{\gamma}}\alpha\left(r^{\frac{\mu-1+\alpha}{\alpha}} - \delta\right)\right]}{(\Pi_2-1)\left[(1-\alpha)rs\left(\mathcal{D}y^{\frac{1}{\mu}}+1\right) + \alpha\left(\mathcal{D}y^{\frac{1}{\mu}}+\mathcal{D}\right)\left(r^{\frac{\mu-1+\alpha}{\alpha}} - \delta\right)\right]^2} \geq 0
$$

$$\text{since } \frac{\partial \mathcal{D}}{\partial \frac{d_1}{\gamma}} = \frac{\partial \left[\frac{(1-s\Pi_2)(\Pi_1-1)}{(1-s\Pi_1)(\Pi_2-1)}\right]}{\partial \frac{d_1}{\gamma}} = \frac{(1-s\Pi_2)(1-s)}{(\Pi_2-1)(1-s\Pi_1)^2}\frac{\partial \Pi_1}{\partial \frac{d_1}{\gamma}} \leq 0$$

$$\frac{\partial y}{\partial \frac{d_1}{\gamma}} = \frac{\partial \left[\left[\left(\frac{e^2}{e^1}\mathcal{D}\right)^{1-\alpha}\frac{\theta^2}{\theta^1}\right]^{\frac{\mu}{\mu-1}}\right]}{\partial \frac{d_1}{\gamma}} = \left[\frac{\theta^2}{\theta^1}\right]^{\frac{\mu}{\mu-1}}\frac{\mu(1-\alpha)}{\mu-1}\left[\frac{e^2}{e^1}\mathcal{D}\right]^{\frac{\mu(1-\alpha)}{\mu-1}-1}\left[\frac{-e^2}{(e^1)^2}\mathcal{D}\frac{\partial e^1}{\partial \frac{d_1}{\gamma}} + \frac{e^2}{e^1}\frac{\partial \mathcal{D}}{\partial \frac{d_1}{\gamma}}\right] \leq 0$$

$$\frac{\partial y^{\frac{1}{\mu}}}{\partial \frac{d_1}{\gamma}} = \frac{1}{\mu}y^{\frac{1}{\mu}-1}\frac{\partial y}{\partial \frac{d_1}{\gamma}} \leq 0 \text{ and } \frac{\partial \mathcal{D}y^{\frac{1}{\mu}}}{\partial \frac{d_1}{\gamma}} = y^{\frac{1}{\mu}}\frac{\partial \mathcal{D}}{\partial \frac{d_1}{\gamma}} + \mathcal{D}\frac{1}{\mu}y^{\frac{1}{\mu}-1}\frac{\partial y}{\partial \frac{d_1}{\gamma}} \leq 0$$

$$\begin{aligned}
\frac{\partial N_2}{\partial \frac{d_1}{\gamma}} &= \frac{\partial \left[\frac{(1-\alpha)(1-s)r}{\left[(1-\alpha)rs\left(\mathcal{D}^{-1}y^{\frac{-1}{\mu}}+1\right)+\alpha\left(y^{\frac{-1}{\mu}}+1\right)\left(r\frac{\mu-1+\alpha}{\alpha}-\delta\right)\right](\Pi_2-1)}\right]}{\partial \frac{d_1}{\gamma}} \\
&= \frac{-(1-\alpha)(1-s)r\left[(1-\alpha)rs\frac{\partial \mathcal{D}^{-1}y^{-\frac{1}{\mu}}}{\partial \frac{d_1}{\gamma}} + \frac{\partial y^{\frac{-1}{\mu}}}{\partial \frac{d_1}{\gamma}}\alpha\left(r\frac{\mu-1+\alpha}{\alpha}-\delta\right)\right]}{(\Pi_2-1)\left[(1-\alpha)rs\left(\mathcal{D}^{-1}y^{\frac{-1}{\mu}}+1\right)+\alpha\left(y^{\frac{-1}{\mu}}+1\right)\left(r\frac{\mu-1+\alpha}{\alpha}-\delta\right)\right]^2} \leq 0 \\
\text{since } \frac{\partial y^{\frac{-1}{\mu}}}{\partial \frac{d_1}{\gamma}} &= -\frac{1}{\mu}y^{-\frac{1}{\mu}-1}\frac{\partial y}{\partial \frac{d_1}{\gamma}} \geq 0 \text{ and } \frac{\partial \mathcal{D}^{-1}y^{\frac{-1}{\mu}}}{\partial \frac{d_1}{\gamma}} = -\mathcal{D}^{-2}\frac{\partial \mathcal{D}}{\partial \frac{d_1}{\gamma}}y^{\frac{-1}{\mu}} + \mathcal{D}^{-1}\frac{y^{\frac{-1}{\mu}}}{\partial \frac{d_1}{\gamma}} \geq 0
\end{aligned}$$

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TABLE 1A: INTER-INDUSTRY WAGE DIFFERENTIALS FROM 1973-1981

Industry	1973	1974	1975	1976	1977	1978	1979	1980	1981
MINING	0.17570	0.18851	0.22051	0.21630	0.17902	0.20263	0.15098	0.25954	0.22241
	(0.03595)	(0.03777)	(0.03710)	(0.04100)	(0.03203)	(0.03340)	(0.03182)	(0.02734)	(0.02729)
CONSTR	0.21950	0.19967	0.17182	0.18173	0.16837	0.11916	0.13848	0.12943	0.12268
	(0.01568)	(0.01647)	(0.01812)	(0.01830)	(0.01561)	(0.01507)	(0.01490)	(0.01422)	(0.01498)
MANUF	0.04094	0.04843	0.04528	0.05285	0.06504	0.06915	0.06889	0.07295	0.07118
	(0.00651)	(0.00697)	(0.00743)	(0.00762)	(0.00696)	(0.00710)	(0.00665)	(0.00618)	(0.00656)
TRANSP	0.13952	0.12264	0.13941	0.15198	0.12011	0.13762	0.08433	0.12756	0.10857
	(0.01537)	(0.01601)	(0.01588)	(0.01630)	(0.01441)	(0.01467)	(0.01350)	(0.01203)	(0.01290)
TRADE	-0.14031	-0.11667	-0.12434	-0.11958	-0.12141	-0.12436	-0.10458	-0.10267	-0.09539
	(0.00790)	(0.00831)	(0.00808)	(0.00844)	(0.00700)	(0.00736)	(0.00695)	(0.00642)	(0.00683)
FINANCE	0.06062	0.06422	0.07053	0.02842	0.04259	0.06834	0.03968	0.02924	0.05585
	(0.01674)	(0.01732)	(0.01712)	(0.01705)	(0.01490)	(0.01544)	(0.01387)	(0.01263)	(0.01306)
SERVICE	-0.05322	-0.08191	-0.04462	-0.05976	-0.05171	-0.06188	-0.06051	-0.07807	-0.08238
	(0.00948)	(0.00973)	(0.00957)	(0.00970)	(0.00841)	(0.00851)	(0.00792)	(0.00686)	(0.00721)

TABLE 1B: INTER-INDUSTRY WAGE DIFFERENTIALS FROM 1982-1990

Industry	1982	1983	1984	1985	1986	1987	1988	1989	1990
MINING	0.26339	0.23934	0.20654	0.27052	0.17485	0.16681	0.26291	0.21627	0.19010
	(0.03006)	(0.03132)	(0.02993)	(0.03414)	(0.03348)	(0.03944)	(0.04039)	(0.03625)	(0.03866)
CONSTR	0.11125	0.11243	0.11717	0.11875	0.12067	0.12114	0.11242	0.09194	0.12739
	(0.01663)	(0.01709)	(0.01553)	(0.01543)	(0.01514)	(0.01570)	(0.01589)	(0.01607)	(0.01641)
MANUF	0.09522	0.08582	0.09115	0.09793	0.08508	0.08697	0.07440	0.08559	0.08435
	(0.00729)	(0.00764)	(0.00728)	(0.00745)	(0.00741)	(0.00746)	(0.00777)	(0.00754)	(0.00822)
TRANSP	0.18219	0.15495	0.13703	0.14397	0.16402	0.14012	0.11755	0.09343	0.10295
	(0.01362)	(0.01400)	(0.01330)	(0.01327)	(0.01323)	(0.01393)	(0.01435)	(0.01427)	(0.01378)
TRADE	-0.13073	-0.11884	-0.12377	-0.13101	-0.12994	-0.12381	-0.13317	-0.12590	-0.12888
	(0.00721)	(0.00769)	(0.00734)	(0.00747)	(0.00717)	(0.00754)	(0.00804)	(0.00778)	(0.00765)
FINANCE	0.05220	0.06170	0.06072	0.03810	0.08024	0.06118	0.09251	0.07348	0.07215
	(0.01365)	(0.01397)	(0.01292)	(0.01322)	(0.01284)	(0.01300)	(0.01340)	(0.01383)	(0.01334)
SERVICE	-0.08305	-0.06821	-0.06652	-0.06306	-0.05866	-0.05504	-0.04745	-0.05553	-0.03165
	(0.00744)	(0.00731)	(0.00702)	(0.00713)	(0.00667)	(0.00692)	(0.00715)	(0.00784)	(0.00684)

TABLE 1C: INTER-INDUSTRY WAGE DIFFERENTIALS FROM 1991-1999

Industry	1991	1992	1993	1994	1995	1996	1997	1998	1999
MINING	0.16923	0.15670	0.29574	0.18339	0.23871	0.12692	0.09028	0.14950	0.17886
	(0.04241)	(0.04032)	(0.04125)	(0.04505)	(0.04534)	(0.05153)	(0.04551)	(0.04568)	(0.05202)
CONSTR	0.11102	0.11688	0.09797	0.09038	0.06835	0.08504	0.10948	0.13262	0.07849
	(0.01717)	(0.01703)	(0.01742)	(0.01834)	(0.01749)	(0.01890)	(0.01726)	(0.01728)	(0.01747)
MANUF	0.09541	0.09797	0.09460	0.08179	0.07874	0.08631	0.07299	0.07677	0.06021
	(0.00832)	(0.00844)	(0.00865)	(0.00907)	(0.00876)	(0.00964)	(0.00963)	(0.00986)	(0.00979)
TRANSP	0.13228	0.12539	0.13199	0.11175	0.08179	0.08985	0.13219	0.06132	0.08367
	(0.01427)	(0.01459)	(0.01514)	(0.01562)	(0.01534)	(0.01652)	(0.01506)	(0.01546)	(0.01597)
TRADE	-0.13598	-0.12187	-0.13375	-0.13732	-0.12193	-0.11021	-0.11858	-0.12026	-0.10948
	(0.00775)	(0.00776)	(0.00776)	(0.00827)	(0.00816)	(0.00848)	(0.00817)	(0.00828)	(0.00816)
FINANCE	0.11002	0.09821	0.10186	0.11382	0.09183	0.08529	0.06949	0.09181	0.08933
	(0.01361)	(0.01349)	(0.01361)	(0.01482)	(0.01387)	(0.01557)	(0.01462)	(0.01478)	(0.01485)
SERVICE	-0.04623	-0.05401	-0.03878	-0.01944	-0.01938	-0.02451	-0.02185	-0.01688	-0.00712
	(0.00675)	(0.00679)	(0.00676)	(0.00695)	(0.00672)	(0.00734)	(0.00686)	(0.00692)	(0.00671)

TABLE 2: INTER-INDUSTRY WAGE DIFFERENTIALS AND THE VARIANCE OF INDUSTRY WAGES

Industry	Avg. Rank of Differential	Average Differential	Variance of Wages
MINING	1.1481	0.1998	0.0382
			(0.0037)
CONSTR	2.7778	0.1250	0.0289
			(0.0028)
MANUF	4.2963	0.0765	0.0137
			(0.0013)
TRANSP	2.5185	0.1229	0.0252
			(0.0024)
TRADE	7.0000	-0.1224	0.0083
			(0.0009)
FINANCE	4.2593	0.0705	0.0110
			(0.0008)
SERVICE	6.0000	-0.0501	0.0128
			(0.0010)

TABLE 3: CYCLICALITY OF DIFFERENTIALS

Industry	α	β	γ
MINING	0.00580	-0.00014	-0.00042
	(0.02740)	(0.01430)	(0.00179)
CONSTR	-0.01160	0.00049	0.00046
	(0.00893)	(0.00468)	(0.00059)
MANUF	0.00744	-0.00058	-0.00050
	(0.00383)	(0.00201)	(0.00025)
TRANSP	-0.00330	0.01010	0.00011
	(0.01310)	(0.00685)	(0.00086)
TRADE	0.00205	-0.00060	-0.00007
	(0.00522)	(0.00273)	(0.00034)
FINANCE	-0.00079	0.00198	0.00015
	(0.00915)	(0.00480)	(0.00060)
SERVICE	-0.00435	0.00297	0.00046
	(0.00575)	(0.00301)	(0.00038)

Table 4.

Model		CPS Data				
Variable	steady state value (%)	Mean (%)	Max. (%)	Min. (%)	Industry	Avg. Rank of Differential
$\frac{N^1}{\sum_{i=1}^7 N^i}$	1	1	2	1	Mining	1.1
$\frac{N^2}{\sum_{i=1}^7 N^i}$	7	7	8	7	Transp.	2.5
$\frac{N^3}{\sum_{i=1}^7 N^i}$	6	6	7	5	Constr.	2.8
$\frac{N^4}{\sum_{i=1}^7 N^i}$	7	7	9	6	Finance	4.3
$\frac{N^5}{\sum_{i=1}^7 N^i}$	26	26	35	19	Manuf.	4.3
$\frac{N^6}{\sum_{i=1}^7 N^i}$	27	27	33	19	Service	6.0
$\frac{N^7}{\sum_{i=1}^7 N^i}$	26	26	27	24	Trade	7.0

Table 5.

Model		CPS Data				
Variable	steady state value (%)	Mean (%)	Max. (%)	Min. (%)	Avg. Rank of Differential	Industry
$\left(\frac{w^1-\overline{w}}{\overline{w}}\right)$	20	20	30	9	1.1	Mining
$\left(\frac{w^2-\overline{w}}{\overline{w}}\right)$	12	12	18	6	2.5	Transp.
$\left(\frac{w^3-\overline{w}}{\overline{w}}\right)$	12	12	22	7	2.8	Constr.
$\left(\frac{w^4-\overline{w}}{\overline{w}}\right)$	7	7	11	3	4.3	Finance
$\left(\frac{w^5-\overline{w}}{\overline{w}}\right)$	8	8	10	4	4.3	Manuf.
$\left(\frac{w^6-\overline{w}}{\overline{w}}\right)$	-5	-5	-8	1	6.0	Service
$\left(\frac{w^7-\overline{w}}{\overline{w}}\right)$	-12	-12	-14	-10	7.0	Trade

where $\overline{w} = \left(\sum_{i=1}^{7} w^i N^i\right) / \left(\sum_{i=1}^{7} N^i\right)$

Figure 1. Differentials and the Unemployment rate

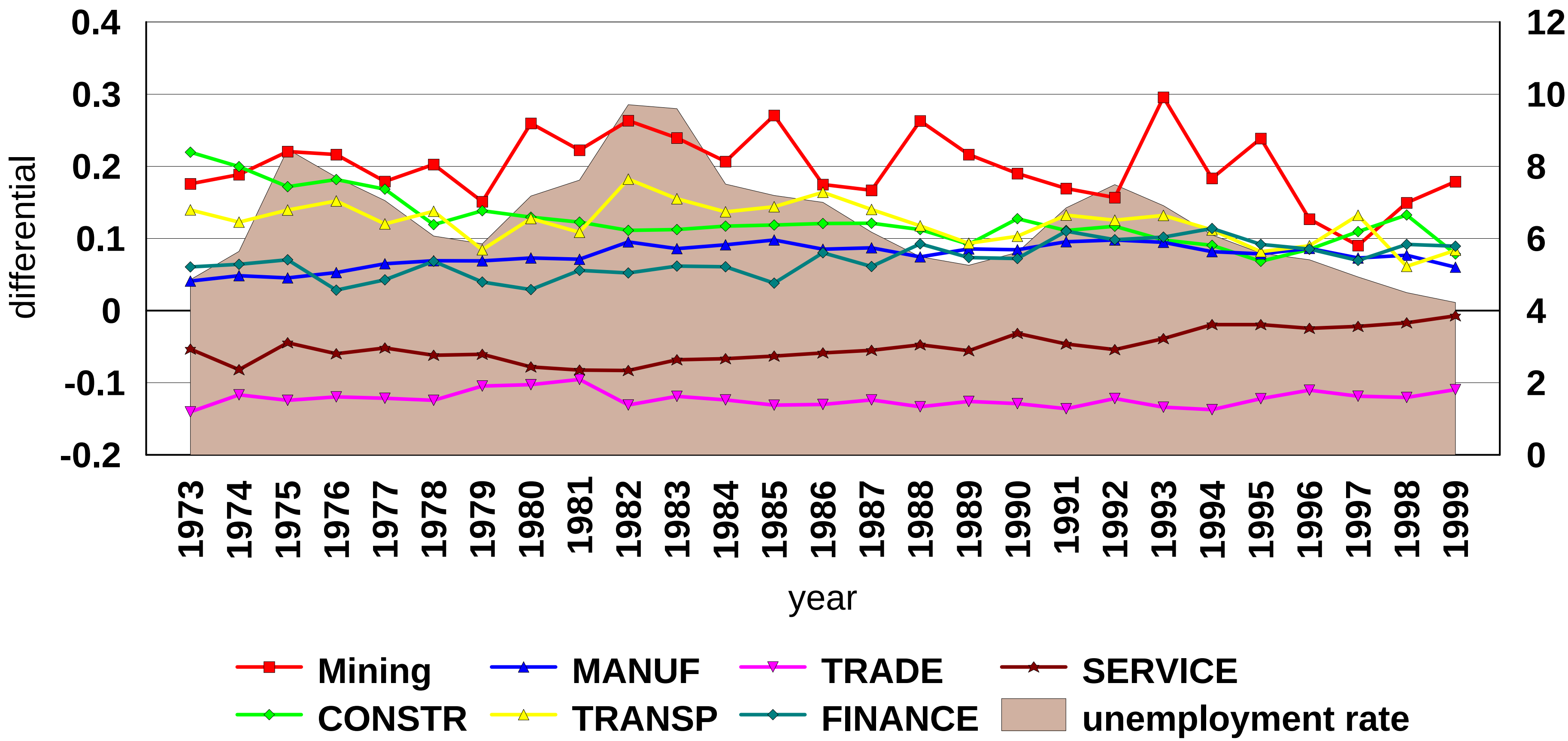

Figure 2. Aggregate Responses to a 1% Positive Technology Shock