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HOW MULTI-TASKING JOB DESIGNS AFFECT PRODUCTIVITY: EVIDENCE FROM AUSTRALIAN COAL MINING INDUSTRY[1]

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After the 1990s, the Australian coal industry vigorously eliminated two types of task demarcations: (I) the demarcation *between* production and maintenance stream tasks and (II) the demarcation *within* the production stream. Using data covering 1985-2005, I estimate the effect of the elimination of these demarcations on productivity, then analyze several explanations for how multi-tasking would affect productivity. The results show that the elimination of 'between' demarcation would increase coal production by 27%, while the elimination of 'within' demarcation has no effect on productivity. Furthermore, the relationship between coal demand uncertainty and the elimination of demarcations is weak. These patterns are inconsistent with a common explanation for how multi-tasking affects productivity: the ability of mines to freely redeploy workers enables mines to fully utilize labor, and to adjust to demand fluctuations. Rather, these results are better explained by the elimination of redundancies: the bundling of 'overlapping tasks' reduces duplication of effort and unnecessary wait time.

The growing body of literature documents the trend of work organizations shifting away from Tayloristic organization, characterized by specialization, towards more flexible structures, involving multi-tasking with less specialized task assignment. Multi-tasking is a situation in which workers are capable of performing several tasks, and may be performing these tasks with some regularity (Lazear 1998). Extensive evidence suggests that multi-tasking is widespread. Machin and Wadhwani (1991) study the effects of unions on organizational changes using British Data[2], showing that 27% of their sample experienced organizational changes such as the elimination of job demarcations. Ichniowski (1992) and Adler et al.

[1]The data, additional results, as well as the Stata commands and the Fortran programs used to generate the results presented in this paper are available from the author upon request.

[2]Workplace Industrial Relations Survey

(1995) provide case studies showing that, by significantly reducing the number of job classifications, firms have increased the use of multi-tasking. Further research shows that multi-tasking is often achieved by job rotation. Using 694 manufacturing establishments in the US, Osterman (1994) shows that nearly 50% of his sample has adopted job rotation. Lindbeck and Snower (2001) present evidence that European firms are moving toward multi-tasking work organizations, with similar evidence from Korea presented by Park (1996).

The widespread use of multi-tasking indicates that the adoption of multi-tasking job design is motivated by its assumed productivity-enhancing effect. However, the existing literature has not provided satisfactory answers to the following two questions. First, *what is the productivity-enhancing effect of multi-tasking?* Katz et al. (1987) examine the effect of multi-tasking job design, such as reduced job classification, on plant-level productivity of a large US automobile producer, but they find that adoption of multi-tasking has no effect on productivity. Cappelli and Newmark (2001) find that job rotation has a negative effect on productivity (see Table 3 of their study). The literature on labor market flexibility typically focuses on the effects that the unions have on the adoption of multi-tasking, or on the substitution elasticities among different inputs (Machin and Wadhwani 1991; Freeman and Medoff 1982; Magnani and Prentice 2006). However, there has not been an estimate of the effect of adoption of multi-tasking on productivity. Other studies have focused on complementarities among different human resources practices (Ichniowski et al. 1997; Macduffie 1995), making it difficult to assess the isolated impact of multi-tasking. Thus, the effects of multi-tasking on productivity has not been well-established.

Second, *what is the mechanism through which multi-tasking job designs affect productivity?* Although there are several studies that examine why some firms adopt 'flexible work practices' while other firms do not (Osterman 1994; Ichniowski et al. 1995; Gittleman et al. 1998; Gale et al. 2002), these studies have not tested existing theories regarding how multi-tasking would affect productivity.

In this paper, I attempt to answer both of the above questions by using an original data set from Australian open cut coal mines covering the period 1985 to 2005. Australia has been the world's largest coal exporter for more than a decade, accounting for nearly 30% of world coal exports in 2006[3]. However, in the 1990s, the Australian coal mining industry was criticized for its inefficiency compared with other coal producers such as the U.S. (Tasman Asia Pacific 1997). Rigid task demarcations were considered by mine managers to be one of the major factors restricting Australian mines' productivity (Productivity Commissions 1998a). Nonetheless, after the bargaining system was decentralized in the 1990s, Australian coal mines vigorously eliminated two types of task demarcation: (I) task demarcation between production stream tasks (equipment operation tasks) and engineering stream tasks (maintenance tasks), and (II) task demarcation within the production stream tasks (tasks associated with different types of equipment). In this paper, I estimate the effects of the elimination of each type of task demarcation on productivity, then analyze the following four possible explanations for how multi-tasking job designs affect productivity. These explanations are derived from economic literature as well as from interviews with mine managers.

First, multi-tasking would affect productivity by eliminating redundancy. A task consists of a series of subtasks. As noted by Lazear (1998:450), when two tasks share a common subtask which can be performed by the same worker at the same time, the bundling of the two tasks would eliminate duplication of effort and unnecessary wait time. Second, multi-tasking would affect productivity by increasing input flexibility; the ability of the mines to reassign workers to different tasks according to production needs. Third, multi-tasking would affect productivity by enhancing task coordination within the production team. As noted by Lazear (1998:446), task coordination is easier if team members know each other's tasks. Fourth, multi-tasking between production and engineering workers may facilitate regular equipment maintenance. Regular maintenance is likely to reduce major machine

[3]Based on OECD International Energy Agency, "Coal Information 2008".

breakdowns, contributing to increased productivity.

The above explanations have different implications regarding (i) the productivity-enhancing effects of the elimination of specific task demarcations, and (ii) the relationship between coal demand uncertainty and the adoption of multi-tasking, giving us some leverage in differentiating between these explanations. Past empirical studies have treated the productivity-enhancing effects of multi-tasking as events occurring inside a black box. The analysis in this paper would open the black box, shedding light on the mechanism through which multi-tasking job designs affect productivity.

It should be noted that the mining industry may not be representative of the whole economy. However, the organizational structure of the mining industry shares important features with other industries, manufacturing in particular. First, the division of work into production and maintenance streams is a common feature of the manufacturing industry. Second, coal extraction is carried out in a team setting. Team production is also a common feature in many manufacturing organizations. Therefore, the shift toward multi-tasking organization in the manufacturing industry would also involve the elimination of the aforementioned two types of task demarcations. Thus, analysis of the mining industry will provide useful insights into other industries.

1 Task demarcation in the Australian coal mining industry

I begin with a description of task demarcations in the Australian coal mining industry, and with a description of how task demarcations were removed. This study utilizes data from 21 open-cut coal mines in Australia for the period 1985 to 2005. The open cut mining method involves removal of the earth above the coal seam. The method generally requires two task streams: one for production and the other for engineering. Workers in the production stream operate three types of equipment; bulldozers, excavators[4], and trucks. Bulldozers are used to level the surface of the coal seams. Excavators are used to extract coal from the coal seam, then load it onto the truck. Trucks are used to deliver coal to the coal washing plant. Workers in the engineering streams maintain the equipment. Maintenance tasks range from major tasks, such as fixing a fuel system, to relatively minor tasks, such as changing the bucket teeth of a bulldozer. Maintenance is usually done at a workshop, however maintenance for unexpected machine breakdowns and lesser tasks are carried out onsite at the coal field as needs arise.

In Australia, there was strict task demarcation *between* the production and engineering streams. Furthermore, there was strict task demarcation *within* the production stream based on the type of equipment a worker operates. Mine managers considered task demarcations to be one of the major factors restricting productivity. Exxon Coal (1998) notes that

> "Australian coal mines fall well short of best practice productivity levels achieved by comparable international coal mines. ... There are a significant number of factors which contribute to this result. ... Among other things, this includes demarcation of work...."

Historically, task demarcations in Australian coal mining can be traced to job-specific union coverage (Barry et al. 1999). However, task demarcations became deeply entrenched in its workplace by various provisions of multi-employer collective bargaining agreements that covered the coal mining industry. Such collective agreements are called the *award* in Australia. The most relevant award in this study is the P&E Award of 1990[5], which covered almost all of the coal mines in Australia in the 1990s. The P&E Award entrenched task demarcations in the following ways. First, it provided a legal basis to task demarcation *within* the production stream. The P&E Award classified production stream tasks into nine

[4]An excavator is a machine with a large size bucket to extract coal. Excavators include shovels, excavators, and draglines.

[5]P&E Award: the Australian Coal Mining (Production and Engineering) 1990 Interim Consent Award

categories based on equipment type and capacity. These narrowly defined job classifications entrenched task demarcation within the production stream. Second, the P&E Award provided a legal basis for the demarcation *between* the production and engineering streams. Clause 31 of the P&E Award, known as the 'customs and practices' provision, gave common, informal work practices in the coal industry legal status, thus providing a legal basis for the demarcation between the two streams.

Nonetheless, the industry gained the opportunity to eliminate task demarcations when the bargaining system was decentralized. First, the Industrial Relations Act of 1988, the Industrial Relations Reform Act of 1993 and the Work Place Relations Act of 1996 came into practice, allowing mines to opt out of the awards. More specifically, these acts allowed mines to negotiate mine-specific collective agreements with employees, allowing mines to alter the award conditions that entrenched task demarcations. Second, the P&E Award included Clause 20, which allowed mines to alter the P&E Award conditions by negotiating mine-specific collective agreements. Mine-specific collective agreements are called '**enterprise agreements**' in order to emphasize the fact that the agreements are negotiated at an enterprise level, not at an industry level. The first enterprise agreements were certified only after 1990. Below, I describe exactly how enterprise agreements eliminated task demarcations.

The elimination of demarcation **within** the production stream was accomplished by the negotiation of a 'work model'. Due to mounting criticism by coal managers concerning the perceived inefficiency of Australian coal mines in the late 1980s, the P&E Award introduced the 'work model' provision. The work model provision allows a mine to reduce job classifications by negotiating a work model with its employees. A work model typically specifies the list of core skills. Jobs may be classified into several levels based on the number of skills a worker possesses, with each level being given a different wage rate. A work model has to be approved by the Coal Industry Tribunal in the form of an enterprise agreement[6]. The

[6]The Coal Industry Tribunal is one branch of the Industrial Relations Commissions which are the indus-

number of job levels is determined by negotiations at each mine. A job design with fewer job levels provides mine managers with greater multi-tasking capability. This point has been made in several enterprise agreements. Bloomfield Colliery's 1992 enterprise agreement reduced its job classification to five levels, noting that "[t]his relatively flat wage structure (thus fewer job levels) will enable employees to be involved in a broad range of tasks (Clause 9.2)."

According to the case study conducted by Barry et al. (1999), multi-tasking within the production stream was rigorously implemented. For example, the Blackwater mine in the State of Queensland adopted a work model in 1992. After the adoption, workers were no longer allocated to a particular job. Instead, they could be allocated at the start of each shift to any job for which they had accredited skills.

The elimination of demarcation ***between*** production and engineering streams was achieved separately from the elimination of the demarcation *within* the production stream, due to one stipulation in the work model. The work model guideline explicitly divides jobs into production and engineering streams. This means that if a mine employs a work model (to eliminate demarcation *within* the production stream), the demarcation *between* the production and the engineering streams will be systematically entrenched. To eliminate the demarcation between the two streams, management had to further negotiate with employees to include a provision that explicitly eliminates the demarcation. For example, the Stratford Mine's 2002 enterprise agreement explicitly states that "...there will be no demarcation of work between production and engineering (Clause 3)".

trial tribunals in Australia.

2 Four possible explanations for how multi-tasking job designs affect productivity

The previous section has shown that the Australian coal industry adopted multi-tasking job designs by eliminating two types of task demarcations; (i) task demarcation *between* the production and engineering streams, and (ii) task demarcation *within* the production stream. The following section will explore how elimination of these task demarcations might affect productivity. From interviews with several mine managers as well as a review of the economic literature, I derived four possible hypotheses. This section details these hypotheses, then shows that these hypotheses have different implications regarding which type of multi-tasking would increase productivity, and which types of mines are most likely to adopt these multi-tasking job designs.

[1] Redundancy elimination

Multi-tasking would enhance productivity through elimination of redundancy. A task consists of a series of subtasks. As explained by Lazear (1998:450), when two tasks share a common sub-task which can be performed by the same worker *at the same time* (when there is a 'task overlap'), bundling of these tasks eliminates a duplication of effort. Moreover, when overlapping tasks are artificially split, one worker needs to pass a part of tasks to another worker, creating unnecessary wait time for the other worker to arrive the site. Bundling of tasks would avoid such a problem.

Interviews with several coal managers revealed that the demarcation *between* the production and engineering streams created artificial redundancy. According to the task demarcation between the production and engineering streams, engineering workers are not allowed to operate machines. Therefore, whenever maintenance requires operation of a machine, a production worker must be present to operate the machine. For example, when engineering workers fix the cylinder of a shovel, a production worker must be on hand to move the shovel into the position for them. If an engineering worker were allowed to operate the shovel, the production worker need not attend the maintenance session. This illustrates how a task that can be performed by one worker at the same time, takes two because of task demarcation. Most of the mine managers that I interviewed suggested that elimination of such redundancy would greatly improve efficiency in the mining industry.

The demarcation between the production and engineering streams also creats unnecessary wait time. Some maintenance tasks are simple enough for production workers to perform. However, under the task demarcation between the two streams, an engineering worker has to be called for, creating unnecessary wait time. An excerpt from Exxon Coal (1998) effectively illustrates this problem.

> "Replacing a trip rope (of a shovel) may require an operator 5 to 10 minutes. Because this is a maintenance issue at our Australian coal mines, the time lost in the call out of maintenance personnel to perform this work typically results in a 30 minute loss of production. Inefficiencies such as these, multiplied many times across many activities at Australian coal industry mine sites, severely impede productivity and cost competitiveness."

The above descriptions show that the elimination of 'between' demarcation would eliminate redundancy. Now let us consider the elimination of demarcation *within* the production stream. Consider the following two tasks within the production stream: power shovel operation and truck driving. The power shovel task consists of two subtasks: (1) extracting coal from the coal seam, then (2) loading it onto the truck. The truck driving task consists of (1) locating the truck so that the power shovel can load the coal and (2) delivering the loaded coal to a coal washing facility. It appears that there is no common subtask that can be performed by the same worker at the same time (i.e., there is no 'task overlap'), since completing the power shovel task would not complete any part of the truck driving task.

The same reasoning would also suggest that there is no task overlap between different tasks within the production stream (i.e., between operation of a power shovel and operation of a bulldozer). This implies that there is no redundancy that can be eliminated by eliminating the task demarcation *within* the production stream.

It should be noted that the absence of task overlap among production tasks does not imply that skills required to perform these tasks do not overlap each other. In fact, there may be a significant overlap among skills required to perform different production tasks. For example, the skills required to drive a power shovel may be very similar to the skills required to drive a truck. However, because one worker cannot operate both pieces of equipment *at the same time*, bundling of these tasks would not eliminate any redundancy.

Thus, the implication of this hypothesis is that 'redundancy elimination' would affect productivity only through the elimination of task demarcation *between* the production and engineering streams.

[2] Input flexibility

Multi-tasking would affect productivity by increasing input flexibility. There are several definitions of input flexibility according to the literature. Flexibility in adjusting the quantity of inputs is one definition. The absence of task demarcation between the production and engineering streams, as noted in the redundancy elimination hypothesis, is also one form of input flexibility. In this paper, however, input flexibility is defined as the ability of a mine to temporarily reassign workers to a task that requires greater manpower and, away from a task requiring less manning, without necessarily changing the size of workforce. The issue of input flexibility, as defined in this study, has attracted much attention from economists. Some studies focus on the effect of input flexibility on the way firms adjust to demand fluctuation (Haskel et al 1997), while others focus on the effect of unionization on the substitution elasticities between different inputs (Freeman and Medoff 1982; Magnani and Prentice 2006).

When I interviewed several mine managers about how multi-tasking would affect productivity at their mines, input flexibility was one of the most common answers. For example, for a production team, some equipment may not be required for the whole shift. Thus, multi-tasking would lead to a better utilization of labor. Some managers assert that multi-tasking is useful in avoiding the impact of absenteeism on production stoppage. Furthermore, input flexibility is useful when there is demand fluctuation, as production needs may change in a demand shock. Since the 1990s, the Australian coal mining industry has faced increased competition in the coal export market from new rivals, such as Indonesia. Therefore, the ability to adjust for demand shocks might be particularly relevant.

Input flexibility is useful to the extent that a worker is capable of performing different tasks. Although it may not be difficult to train engineering workers to operate machines for maintenance purpose (such as changing the position of a machine), it would still be difficult to train them to competently undertake the whole production process. Such training would require engineering workers to make frequent trips to the coal field. On the other hand, it would be much easier to train production workers to operate other types of equipment. Thus, I expect that input flexibility would affect productivity mainly through the elimination of task demarcation *within* the production stream. In fact, when mine managers refered to the usefulness of input flexibility, they often provided examples of workers *within* the production stream operating different types of equipment. For example, the CEO of Wesfarmers describes the flexibility in his newly acquired Curragh mine in 2000 as

> "Working arrangements are very flexible as multi-skilling arrangements are in place. There are no demarcation issues at the mine. For example, an operator will hop off one piece of equipment and operate another while somebody is at their break (AAP Information Services Pty. Ltd. 2000)."

Nonetheless, we cannot eliminate the possibility that engineering workers are reassigned to a production task. Another way to examine the validity of the input flexibility hypothesis is to look at who has adopted the multi-tasking job designs. Input flexibility would be more useful in a mine facing greater demand fluctuation. In the empirical section, I use coal qualities as proxies for coal demand uncertainty (thus proxies for demand fluctuation). Coal quality is generally measured by the amount of impurities, such as ash, moisture, volatile matters and sulphur. The greater the level impurity, the lower the coal quality. Although much Australian coal is purchased on long term contracts, low quality coal is more likely to be purchased in the spot market rather than on long term contract (Productivity Commission 1998b:D15). Thus, mines with low coal quality face greater demand uncertainty. The input flexibility hypothesis predicts that mines with lower coal quality are more likely to adopt both types of multi-tasking.

Thus, the input flexibility hypothesis has two implications. First, input flexibility would affect productivity mainly through the elimination of demarcation 'within' the production stream. Second, mines with low coal quality are more likely to adopt both types of multi-tasking. However, the prediction regarding the productivity-enhancing effect of the elimination of 'between' demarcation is ambiguous.

[3] Enhanced task coordination

Multi-tasking may affect productivity by enhancing task coordination among production team members. As noted by Lazear (1998:446), task coordination is easier if team members know each other's tasks. Better task coordination would translate into higher productivity. This hypothesis is particularly applicable to multi-tasking *within* the production stream due to the use of team work within the production stream. Coal extraction is typically performed by a team of 5 production workers. For example, a shovel operator excavates coal, then loads it directly onto a truck. According to mine managers, if a truck driver does not position the truck properly, the shovel operator has to move the whole shovel to load the coal, causing inefficiency. Learning each other's task would enable a better coordination of these tasks. In contrast, a team structure seems to be absent between production and engineering workers. Interaction between production and engineering workers occurs only when a production worker has to call a maintenance crew to handle unexpected mechanical problems. Therefore, the necessity of task coordination between production and engineering workers would be far less frequent than among the production team members. Thus, 'enhanced task coordination' should affect productivity mainly through the elimination of 'within' demarcation, but the prediction regarding the productivity-enhancing effect of 'between' demarcation is ambiguous.

[4] Better machine maintenance

During one interview, it was mentioned that multi-tasking *between* production and engineering streams would benefit mines by facilitating more regular machine maintenance. The elimination of 'between' task demarcation would enable production workers to perform some maintenance tasks regularly, such as fault checking. Regular maintenance should reduce the probability of major machine breakdowns, which would translate into higher productivity. Thus, this hypothesis implies that elimination of task demarcation between the production and engineering streams would have a positive effect on productivity.

3 Estimation methods

The existing literature has employed two competing methods to estimate the effect of "innovative work practices" on productivity. The first method is to specify a model in which the introduction of a new work practice affects output per worker. This method is used by Cooke (1994) and Macduffie (1995). Since output per worker is a standard measure of labor productivity, this method has an intuitive appeal. A disadvantage, however, is its implicit assumption that the introduction of a new work practice only affects labor productivity, neglecting the possibility that it may affect capital productivity as well. The second method is to estimate a Cobb-Douglas or translog production function in which the introduction of a new work practice affects the intercept of the production function. This method is used by Hamilton et al. (2003) and Hempell (2005). In this specification, the introduction of a new work practice affects both output per worker and output per capital by shifting the entire production function. The fact that this method only allows a work practice to affect the intercept may be restrictive. However, I use the second method since multi-tasking job designs may affect not only output per labor but also output per capital by facilitating an efficient utilization of equipment.

3.1 The definitions of multi-tasking and other work practice variables

Based on the discussions in Section 1, the reduction in the number of job classifications is a reasonable variable that represents the elimination of the demarcation **within** the production stream. The maximum number of job classifications is nine, as given by the P&E Award standard job classifications. Thus, I define a variable, (ClassRedu), by

(ClassRedu) = 9 − (the # of job classifications in the enterprise agreement)

I constructed a binary variable, ($MultiBetween$) that attempts to show a genuine elimination of demarcation **between** the production and engineering streams by using the following three criteria.

(MultiBetween) =1 (1) if the mine explicitly requires production and engineering workers to multi-task across the streams, (2) if the mine eliminates the distinction between the production and engineering work, and at the same time, explicitly requires an employee to undertake any tasks that are allocated by the employer, or (3) if the mine allows production and engineering workers to cross-train their core skills. If neither (1), (2) nor (3) holds, this variable takes the value 0.

In order to separate the effect of multi-tasking from other changes in work practices, I examined enterprise agreements to find various changes in work practices that would affect productivity. Table 1 shows the definitions of these work practice variables. Most notably, these mines began to eliminate restrictions placed on the hiring and redundancy practices. The P&E Award stipulates that mines should hire previously retrenched workers first when increasing employment (Clause 27). The P&E Award also requires that mines should first make redundant workers whose tenure is the shortest when reducing employment (Clause 24). (Staff) is equal to 1 if only one of these restrictions is removed, 2 if both restrictions are removed, and 0 otherwise. Thus, (Staff) captures the effect of flexibility in adjusting the employment size.

3.2 The production function estimation

The following is the basic production function specification.

$$\begin{aligned} log(Output)_{it} &= \beta_1(MultiBetween)_{it} + \beta_2(ClassRedu)_{it} \\ &+ \gamma'(Input\ Variables)_{it} + \theta' X_{it} + c_i + \mu_{it} \end{aligned} \quad (1)$$

where i denotes the mine, and t denotes the time period. Output is measured by annual saleable coal production. The basic model is a translog production function where log of input variables as well as their squares and cross products are included. Table 1 shows the definition of input variables. The coefficient, β_1, captures the effect of multi-tasking *between* the production and engineering stream tasks, while β_2 captures the effect of multi-tasking *within* the production stream.

X_{it} is the vector of all other control variables listed in Table 1. Log of the thickness of the seams is included as a thinner seam would negatively affect the output. To separate the effects of multi-tasking from other work practices, various work practice variables are included. Some mines were owned by foreign companies, notably the Oil Majors[7] and Japanese companies. To capture a possible managerial efficiency (or inefficiency) of these

[7]Shell, BP, Exxon and Esso

foreign companies, I include Oil-Major ownership, Japanese ownership and their squares in the model. Productivity may increase over time due to unobserved technological changes. To capture such effects, I include a time trend variable t and its square. To control for year specific productivity shocks, I include year dummy variables. The term, c_i, is a mine-specific time invariant unobserved effect that would affect coal production. A possible correlation between c_i and other explanatory variables causes biases in the ordinary least square estimation (OLS). Thus, we apply the fixed effect estimation to this model.

3.3 Instrumental variable estimation using coal qualities

If multi-tasking variables are correlated with the idiosyncratic error term, μ_{it}, the fixed effect estimation of β_1 and β_2 could be still biased. Such correlations may occur if there is a time varying unobserved effect that affects both production and the multi-tasking variables. One such time varying unobserved factor could be the union density at each mine. Since unions have strongly opposed the elimination of demarcations (Productivity Commission 1998a:123), union density would be negatively correlated with the adoption of multi-tasking. At the same time, union density would directly affect productivity. If the union effects on productivity are negative as documented by (Mitchell and Stone 1992; Bemmels 1987), this would introduce a positive bias in the estimate of multi-tasking, since less-unionized (thus more productive) mines are more likely to adopt multi-tasking job designs.

I address the above issues by using instrumental variable estimation. Valid instruments should be correlated with multi-tasking variables, but not with time varying unobserved effects such as union density. The instrumental variables are the coal quality variables, listed in Table 1. Coal qualities are measured by the impurity contents of the coal. As noted in the description of the input flexibility hypothesis, mines with low coal quality may be more likely to adopt multi-tasking variables. It is unlikely, however, that coal quality has a direct impact on union density[8]. Table 2 shows the descriptive statistics of the coal quality variables. Coal quality data are derived from the NSW Coal Industry Profiles[9] and the Coal Year Books[10]. We instrument the demeaned multi-tasking variables with demeaned instrumental variables in the two stage least square (2SLS) procedure. Coal qualities change over time, since the coal seams that are mined at a particular mine change over time.

We use the Kleibergen-Paap rank test (Kleibergen and Paap 2006) to test the relevance of instruments, and Hansen's J statistic to test the overidentifying restrictions. We also test if multi-tasking variables can be treated as exogenous, since treating endogeneity when it is actually exogenous is costly in terms of precision.

3.4 Data and descriptive statistics

Multi-tasking variables and other work practice variables are constructed by examining the enterprise agreements. Since equipment data is only available for mines in the state of New South Wales (NSW), data collection was confined to just those mines. All the enterprise agreements certified after 1996 are available online[11]. Enterprise agreements certified before 1995 are obtained from the Australian Industrial Registry. The total number of enterprise agreements used in the study is 97.

Table 1 shows the definitions of all the variables used in this study. The dependent variable is the log of annual saleable coal production at each mine. We have four input variables. Employment is measured by the number of employees. Bulldozer usage is measured by the sum of engine capacities. Truck usage is measured by the sum of loading capacities. Excavator usage is measured by the sum of bucket sizes. Production and employment data are provided by Coal Service Pty Ltd. NSW Coal Industry Profiles and Coal Year Books contain yearly information about the equipment models as well as the number of each model

[8]If unions attempt to increase their membership in mines with higher coal qualities, coal qualities may not be good candidates for instruments. Thus, the validity of these instruments will be formally tested.

[9]Published annually by NSW Department of Mineral Resources.

[10]Published annually by the Joint Coal Board.

[11]http://www.wagenet.gov.au

of equipment used by a particular mine[12]. Capacity information of each piece of equipment, such as the engine capacities of bulldozers, has been obtained by directly contacting manufacturers, or via the manufacturers' websites.

Data collection is confined to the mines that have operated at least some years during the 1990s, since this is the period in which drastic changes in the bargaining system occurred. Among those mines, there were some mines that first opened during the sample period. For these, I dropped the first two years of observations, assuming new mines do not immediately reach 'normal' operating conditions. In addition, since the NSW Coal Industry Profile was not published in 1987-1988, these years are excluded from our sample. The final sample contains 288 mine-year observations, containing 21 open-cut mines during the period 1985 to 2005. Table 2 contains descriptive statistics. It is worth noting the size of the sample. The number of observations, 288, may appear to be rather small. Nevertheless, my sample includes, on average, 84% of all the open-cut coal production in NSW for the period, with NSW accounting for about 35% of all the open cut coal production in Australia in 2000. Moreover, a small number of cross-sectional units is not uncommon for industry specific research. For example, in a study of the productivity effect of human resource bundles in US steel plants, Ichniowski et al. (1997) used 35 cross-sectional units over a 5-year period.

Figure 1 shows the sample average of the work practice variables by year. By 2001, the sample average of (ClassRedu) is close to 6. Since a mine usually differentiates induction level jobs from ordinary jobs, the maximum (ClassRedu) is 7. This means that most mines have significantly eliminated task demarcation within the production stream by 2001. As for the demarcation between the production and engineering streams, only 18% of the mines eliminated such demarcation by 2000. Nonetheless, by 2005, nearly 70% of the mines eliminated such demarcation.

[12]For example, these reports may show that a particular mine has 3 pieces of Caterpillar D11. Caterpillar D11 is a large size bulldozer.

4 Estimation results

4.1 Checking the quality of instruments and possible exogeneity of multi-tasking variables

Estimated coefficients for the first stage regressions are shown in Table 4 (see, fixed effect results). The null hypothesis that the coefficients for the excluded instruments are jointly equal to zero is rejected for both (MultiBetween) and (ClassRedu) at the 5% significance level (F statistics are 3.4 and 6.9 respectively). The Kleibergen-Paap rank test also rejects the null-hypothesis that model is underidentified at the 1% significance level (p-val=0.0015). For both of the first stage equations, (Ash) and its square are not significant at the 5% significance level. However, the redundancy test proposed by Breusch et al. (1999) rejected the redundancy of these variables (p-val=0.0007). Based on the relevance of instruments, we next test the overidentifying restrictions. Hansen's J statistic is 12.3, with a degree of freedom equal to 7 (p-val=0.09). Thus, at the 5% significance level, the test does not reject the validity of instruments (that is, instruments are uncorrelated with the error terms). The relatively small p-value may be a source of concern. However, this is probably due to the small sample size. When I used the Cobb-Douglas specification instead, p-value for the above null hypothesis increased to 0.61, providing additional support for the validity of the instruments (results are not reported). Based on the validity of the instruments, I test whether the multi-tasking variables can be treated as exogenous. The test statistic is the C-statistic as described by (Hayashi 2000:220) which follows $\chi^2_{(2)}$ distribution in this case. The test statistics is 2.77 (p-val=0.25). Thus, the test rejects the endogeneity of the multi-tasking variables (i.e., does not reject the exogeneity of the multi-tasking variables), indicating that the multi-tasking variables should be treated as exogenous. When the Cobb-Douglas specification is used, endogeneity is also rejected (p-value=0.90, full results are not reported).

One may be concerned that the instruments are weak, possibly leading to the rejection of endogeneity. In fact, Shea's partial R squares for both (*MultiBetween*) and (*ClassRedu*) are small as reported in Table 4 (0.08 and 0.21 respectively). In order to further examine the endogeneity of the multi-tasking variables, I have estimated, jointly, the following three equations that explicitly account for the correlations of the error terms among the production function and the first stage regressions.

$$log(\ddot{Output})_{it} = \beta_1(Multi\ddot{B}etween)_{it} + \beta_2(Class\ddot{s}Redu)_{it} + \gamma' \ddot{Z}_{it} + (\rho_1 \chi_i + e_{it}^{(1)}) \quad (2)$$

$$(Multi\ddot{B}etween)_{it} = \psi_{11}' \ddot{Z}_{it} + \psi_{12}'(Instru\ddot{m}ents)_{it} + (\rho_2 \chi_i + e_{it}^{(2)}) \quad (3)$$

$$(Class\ddot{s}Redu)_{it} = \psi_{21}' \ddot{Z}_{it} + \psi_{22}'(Instru\ddot{m}ents)_{it} + (\rho_2 \chi_i + e_{it}^{(3)}) \quad (4)$$

Double dots indicate that the variables are demeaned. The term, Z_{it}, is the vector of all other variables included in the production function. The term, (*Instruments*), is a vector of coal quality variables. The variable, χ_i, is the i^{th} mine specific unobserved variable that affects all the equations. The coefficient, ρ_j for j=1,2,3, are the factor loads on the unobserved variable. The terms, $e_{it}^{(j)}$ for j=1,2,3, are the usual disturbance terms which are assumed to be independent for all i, t and j, and assumed to be uncorrelated with all the regressors. Since χ_i is not observed, $(\rho_j \chi_i + e_{it}^{(j)})$ are the error terms. Thus, these equations are identical to the first and second stage regressions in the 2SLS procedure, except that the error terms are now decomposed into two terms. A possible correlation among the error terms is captured by χ_i when the factor loads, ρ_j, are not jointly equal to zero. Since endogeneity of the multi-tasking variables is caused by the correlations among the error terms, we can test the endogeneity by testing the null hypothesis that all the ρ_j for j=1,2,3, are simultaneously equal to zero. Under this null hypothesis, the multi-tasking variables are exogenous. Thus, the *failure* to reject this null means that multi-tasking variables are exogenous. I estimate all the equations jointly by maximum likelihood estimation assuming that χ_i are distributed normally with mean zero and variance one, and that $e_{it}^{(j)}$ are distributed normally[13]. The likelihood function is shown in the appendix.

Table 3 shows the maximum likelihood estimation results (see M.LIK). The estimated ρ_j are extremely small and statistically insignificant (ρ_1=-2^{-18}, ρ_2=-4^{-19}, ρ_2=-3^{-18}). Other coefficients are almost identical to the fixed effect results (FE.1). The $\chi^2_{(3)}$ statistic for the null hypothesis that all ρ_j are simultaneously equal to zero was 0.31. Thus, we do not reject this null hypothesis, indicating that the multi-tasking variables are *exogenous*. The fixed effect, again, appears to be the most preferred method.

The rejection of the endogeneity of the multi-tasking variables is not unreasonable judging from circumstantial evidence. The possible presence of unobserved time varying heterogeneity, such as union density, was one reason I suspected the endogeneity of the multi-tasking variables. However, according to the Productivity Commission (1998b:C12), union density for the whole Australian coal mining industry was above 92% between 1986 and 1998. Such high unionization suggests that there was not a significant variation in the union density among mines, which eliminates one reason to suspect the endogeneity of multi-tasking.

4.2 Estimated effects of multi-tasking on productivity

Table 3 reports selected coefficients for the estimation results of the translog production function. All other coefficients are presented in Table 6. The model, FE.1, is the basic fixed effect model. When fixed effects are controlled for, the coefficient for (MultiBetween) drops slightly from 0.32 to 0.29. In contrast, the coefficient for (ClassRedu) drops significantly from 0.049 to 0.017, a more than 60% drop in coefficient. The results for 2SLS model deviate considerably from that of the fixed effect model. However, the endogeneity of multi-tasking variables is rejected, as noted in the previous section. The estimated coefficients for the maximum likelihood estimation (M.LIK) are almost identical to the fixed effect coefficients

[13] I correct the estimated standard errors by multiply them by $\sqrt{(N-\#ofparameters)/(N-\#ofparameters-\#ofmines)}$ to account for the fact that all the variables are demeaned.

(FE.1), further increasing our confidence that multi-tasking variables can be treated as exogenous. Thus, interpretation of the results will be based on the fixed effect results.

Based on FE.1, multi-tasking ***between*** production and engineering streams has a significant impact on productivity. The estimated coefficient for (MultiBetween) indicates that eliminating the demarcation between the production and engineering streams would increase saleable coal production by as much as 29%, after controlling for fixed effects, and holding all other variables constant. In contrast, I did not find evidence that elimination of demarcation ***within*** the production stream increases productivity. Although the sign of the coefficient for (ClassRedu) is positive (0.017), it is not statistically significant at any of the conventional significance levels.

I also estimated fixed effect models for two other data specifications in order to check for robustness. The model, FE.2, drops all the observations in and after year 1998. In July 1998, the industrial tribunal of Australia[14] eliminated various clauses from the P&E Award, such as the clauses restricting hiring and redundancy practices. This incidence is referred to as 'Award Simplification' (Production Commission 1998a:74). Although I believe that the effects of 'Award Simplification' are properly captured by various work practices variables included in the model, it may be possible that some important changes are not fully captured by these variables. Since the adoption of (MultiBetween) accelerated after 1998, it is possible that (MultiBetween) captures 'Award Simplification' effects, rather than the effect of multi-tasking. In order to eliminate such possibility, I dropped observations from 1998 onward. As such, the coefficient for (MultiBetween) increased slightly to 0.33, remaining statistically significant. The coefficient for (ClassRedu) also increased slightly to 0.02, but remains statistically insignificant.

The FE.3 model drops mines that have contracted out all the production and engineer-

[14] The Australian Industrial Relations Commissions, which was formally called the Industrial Relations Commissions.

ing tasks to coal contractors. For all-contracted mines, the frequency of agreement updates appears to be lower than non-contracted mines. Non-contracted mines usually update enterprise agreements every 2 or 3 years. However, for some of all-contracted mines, enterprise agreements were left un-updated for nearly 5 years[15]. This raises the concern that, in all-contracted mines, various changes in work practices may occur through informal channels rather than through enterprise agreements. This could cause miscoding of the multi-tasking variables. To eliminate the possibility that my results are driven by miscoding, I drop all-contracted mines from the data. The effect of (MultiBetween) increased slightly to 33%, and is statistically significant at the 1% significance level. The coefficients for (ClassRedu) dropped significantly to 0.004, however.

The last column of the Table 3 allows for dynamics by including a lag of the output variable. Estimation is based on the GMM procedure proposed by Arellano and Bond (1991). The validity of this model hinges on the assumption that there is no serial correlation greater than the lag of 2. The Arellano and Bond m_2 statistic does not reject the *absence* of serial correlation at the lag of 2 at any of the conventional significance levels (p-value=0.37), thus validating the model. The estimated coefficient for (MultiBetween) is 0.27 and highly significant, while the estimated coefficient for (ClassRedu) is small (0.006) and statistically insignificant.

Choosing the Cobb-Douglas production function instead of the translog production function does not significantly alter the results, neither qualitatively nor quantitatively. Coefficients and standard errors for (MultiBetween) in the Cobb-Douglas specifications are 0.29(0.12), 0.38(0.16), 0.33(0.17), and 0.21(0.09) for FE.1, FE.2, FE.3 and GMM models respectively, all of them statistically significant at the 5% level. The coefficients for (ClassRedu) are not statistically significant for any of the models, however (results are not reported).

[15] For example, Liddel Mine's 2000 enterprise agreements with the coal contractor Hunter Valley Earth Moving Company were not updated until 2005.

For all of the fixed effect and the dynamic specifications, multi-tasking *between* the production and engineering streams appears to have a large effect on productivity, while the effect of multi-tasking *within* the production stream is small and statistically insignificant. The estimated coefficient for (MultiBetween) suggests that the elimination of task demarcation between production and engineering streams would increase saleable coal production by 27% to 33%, all else held constant. This effect is surprisingly large when compared to past studies concerning multi-tasking. Katz et al. (1987) did not find evidence that multi-tasking job designs, such as reduced job classifications, would enhance productivity. Cappelli and Neumark (2001) found that job rotation had a negative effect on productivity (see Table 3 of their study). The literature on labor market flexibility does not offers estimates for the effects of multi-tasking on productivity (Machin and Wadhwani 1991; Freeman and Medoff 1982). Thus, my result provides fresh evidence that multi-tasking has a large impact on productivity.

Finally, the coefficient for (Staff) is statistically significant for all the fixed effect and dynamic specifications (except for FE.2), ranging from 0.14 to 0.18. The coefficient of 0.14 means that the elimination of both hiring and redundancy restrictions would increase coal production by 0.14×2=28%. Thus, flexibility in adjusting the number of employees has a significant effect on productivity. The coefficient for production bonus is also statistically significant for most of the fixed effect and dynamic specifications, ranging from 0.07 to 0.18.

5 How multi-tasking job designs affect productivity

Based on the estimated results, I analyze the four possible hypotheses for how multi-tasking affects productivity. Among these hypothesis, only two are supported by the data. First, the redundancy elimination hypothesis is supported by the results. As explained in Section 2, we expect that redundancy elimination affects productivity only through multi-tasking *between* the production and engineering streams. Thus, the strong effect of (MultiBetween) coupled with the small and insignificant effect of (ClassRedu) is consistent with this hypothesis. When the Australian coal mining industry was criticized for its perceived inefficiency in the 1990s, most of the complainants by mine managers were that such demarcations created artificial redundancies (Productivity Commission 1998a:124). Our results show that mine managers' concerns were indeed valid.

Second, the better machine maintenance hypothesis implies that the effect of 'between' multi-tasking is positive (See Section 2). Thus, the positive and significant effect of (Multi-Between) supports (or does not reject) the hypothesis. Nonetheless, to what extent the elimination of 'between' task demarcation reduces major machine breakdowns remains an empirical question, since we do not have data for machine breakdown frequencies. If multi-tasking does not decrease major machine breakdowns significantly, then the strong effect of (MultiBetween) should be attributed to the redundancy elimination explanation.

The input flexibility hypothesis is not supported by the data. As noted in Section 2, this hypothesis implies that (i) input flexibility affects productivity mainly through the elimination of task demarcation *within* the production stream, and (ii) mines with low coal quality are more likely to adopt both types of multi-tasking. Thus, the small and insignificant effect of (ClassRedu) is not consistent with the first implication. Table 4 shows the estimated effects of coal qualities on the adoption of multi-tasking variables. The effects of coal qualities on (MultiBetween) are estimated using a Logit model as well as OLS and a fixed effect model. The effects of coal qualities on (ClassRedu) are estimated using OLS and fixed effect. These models use individual coal quality variables as well as (SumImpurities) which is the sum of all the individual coal impurity variables. The coefficients for coal quality variables are jointly statistically significant at the 1% significance level for all the models, except for (ClassRedu) when (SumImpurities) is used as the coal quality variable.

The presence of square terms makes it difficult to assess the impact of coal quality on the adoption of multi-tasking. Thus, partial effects are computed and presented in Table

5. Many partial effects show the expected positive sign, i.e., higher impurity contents are associated with greater use of multi-tasking. Nonetheless, there are a non-trivial number of cases where partial effects show negative signs (for example, Sulphur for MultiBetween, SumImpurities, Sulphur and Moisture for ClassRedu). Therefore, the evidence is not strong enough to conclusively support the second prediction of the input flexibility hypothesis.

It is surprising that one of the most common explanations for how multi-tasking affects productivity is not supported by the data. This may mean that mines are using other methods to adjust for demand fluctuation. When one mine supervisor at the Liddell Mine was asked how a mine would adjust to demand fluctuation, he mentioned that the common methods are adjusting inventories, changing overtime, changing the number of rosters, working weekends, or layoffs. Because mines can use these methods, input flexibility may not have been the most effective method to adjust for demand fluctuation.

Finally, the insignificant effect of (ClassRedu) is inconsistent with the enhanced task coordination hypothesis, as enhanced task coordination is expected to affect productivity mainly through multi-tasking *within* the production stream.

6 Conclusion

After the 1990s, the Australian coal industry eliminated two types of task demarcations: (I) the demarcation *between* the production and maintenance stream tasks and (II) the demarcation *within* the production stream. Using data covering 1985-2005, I estimated the effect of the elimination of these demarcations on productivity, then analyzed several explanations for how multi-tasking would affect productivity. The results show that the elimination of 'between' demarcation would increase coal production by 27% to 33%, while the elimination of 'within' demarcation has no effect on productivity. These patterns are not consistent with the most common explanation for how multi-tasking affects productivity: input flexibility. This study demonstrates that input flexibility affects productivity mainly through the elimination of the 'within' demarcation. The insignificant effect of the elimination of the 'within' demarcation is, thus, inconsistent with the input flexibility hypothesis. Furthermore, the correlation between demand uncertainty and the adoption of multi-tasking was weak, leading to the rejection of that hypothesis. These patterns are better explained by the redundancy elimination hypothesis; the bundling of 'overlapping tasks' reduces duplication of effort and wait time. It has been shown that the 'between' demarcation creates artificial redundancy such as requiring production workers to attend maintenance sessions, but the 'within' demarcation does not necessarily create such a redundancy. The strong effect of 'between' multi-tasking, coupled with the small and insignificant effect of 'within' multi-tasking is, thus, consistent with the redundancy elimination hypothesis. In addition, the results are also consistent with the hypothesis that multi-tasking affects productivity by facilitating more regular machine maintenance, but inconsistent with the hypothesis that multi-tasking affects productivity by improving task coordination among production team members.

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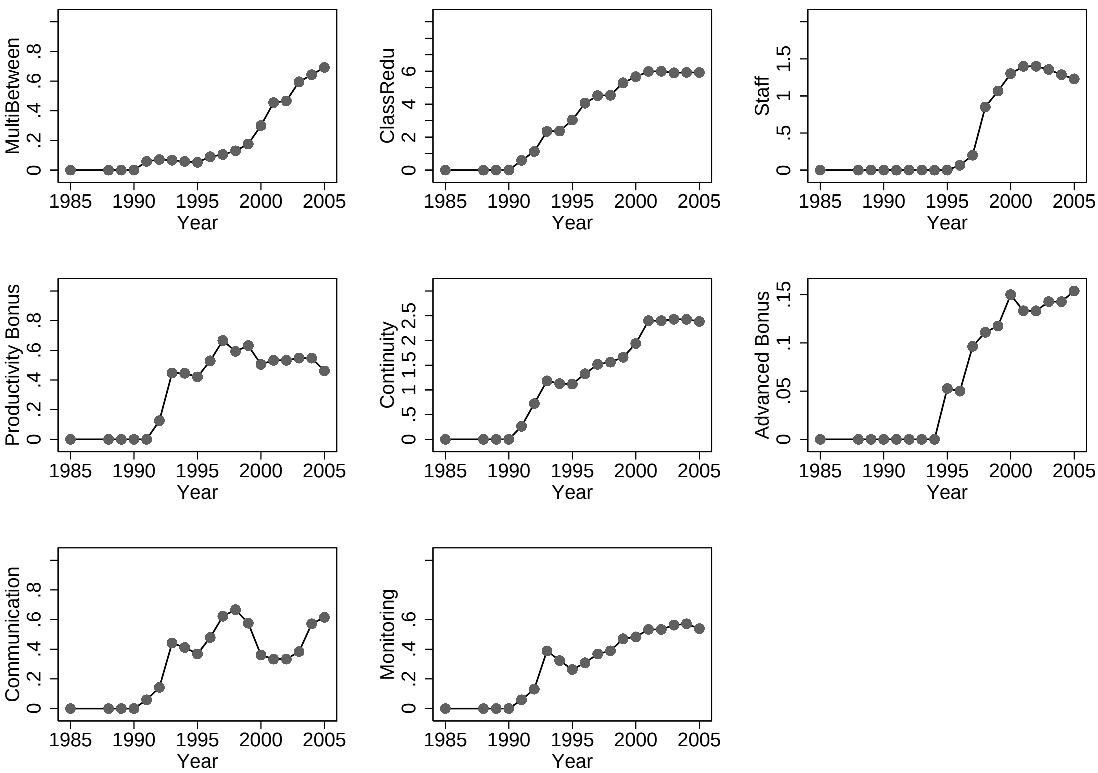
Table 1: Definitions of variables

Variables	Definitions
Other work practice	**variables**
(Staff)	Sum of the following variables. (Flex_hire)=1 if eliminate hiring restriction. (a) (Flex_redun)=1 if eliminate redundancy restrictions. (b)
(Productivity_bonus)	1 if a mine employs a mine-wide bonus where all workers receive equal piece rate depending on mine level coal production.
(Continuity)	Sum of the three dummy variables below. (Staggered_break)=1 if the enterprise agreement requires staggered meal breaks to ensure continuity of operations. (Hot_seat_change)=1 if the enterprise agreement requires staggered shift changes to ensure continuity of operations (Shift12)=1 if 12-hour shift is possible.
(Communication)	1 if regularly held labor management meeting exists.
(Monitoring)	1 if individual performance appraisal or team-based monitoring system exists.
(Advanced_bonus)	Sum of the following variables: (Indiv_bonus)=1 if individual performance-based bonus exists; (Profit sharing)=1 if it exists.
(No_Custom)	1 if the mine eliminates 'Customs and Practices' provision.
Dependent, inputs,	**and other control variables**
(Output)	Annual saleable coal production in millions of tonnes.
(Employment)	Number of employees during the fiscal year.
(Excavator)	Sum of the bucket capacities (in m^3) of excavating equipment.
(Bulldozers)	Sum of engine capacities (in kilowatts) of bulldozers.
(Trucks)	Sum of the loading capacities of trucks (in tonnes).
(Thickness)	Average thicknesses of coal seams currently mined.
(Oil-Ownership)	Oil Majors' ownership (Shell, Exxon, BP & Esso) in (%/100).
(JPN Ownership)	Japanese ownership in (%/100).
Coal quality	**variables**
(Ash)	Air dry ash content of coal in %.
(Sulphur)	Air dry sulphur content of coal in %.
(VolatMatter)	Air dry volatile matter content of coal in %.
(Moisture)	Air dry moisture content of coal in %. (c)
(Moisture info missing)	Dummy variable indicating moisture information is missing.

(a)P&E Award required that mines should hire previously retrenched worker first when increasing employment (Clause 27). (b)P&E Award required that mines should first make redundant workers whose tenure is the shortest when reducing employment (Clause 24). (c) Whenever the moisture information is missing, the mine average of (Moisture) is imputed.

Figure 1:



This figure shows the trend in yearly average of work practice variables over our sample period

Table 2: Summary statistics for selected variables

Variables	Obs	Mean	St Dev	Min	Max
Multi-tasking and work practice variables					
MultiBetween	288	0.20	0.40	0	1
ClassRedu	288	3.49	2.78	0	7
Staff	288	0.53	0.80	0	2
Product_Bonus	288	0.39	0.48	0	1
Continuity	288	1.33	1.10	0	3
Advanced_Bonus	288	0.07	0.25	0	1
Communication	288	0.36	0.47	0	1
Monitoring	288	0.32	0.46	0	1
No_Custom	288	.49	.50	0	1
Dependent and control variables					
Output	288	2,941.3	2,407.8	130	13,749.02
Employment	288	279.7	212.6	20	1,160
Excavator	288	149.1	93.8	13.8	572.9
Bulldozer	288	4,003.5	2,490.33	522	15,918
Trucks	288	3,281.42	2,461.65	180	12,530
Thickness	288	3.10	1.88	1.27	10
Oil-Ownership	288	0.08	0.26	0	100
JPN ownership	288	0.17	0.28	0	1
Coal quality and instrument					
Ash	288	12.91	5.80	8	35
VolatMatter	288	33.14	2.47	23	38.25
Sulphur	288	0.69	0.21	0	1.65
Moisture	288	3.36	2.01	2	10
(Moisture info missing)	288	0.24	0.43	0	1

a. In Australia, fiscal year starts on July 1st. When a new enterprise agreement has not started at the same time with the fiscal year, the values of the work practice variables are the fraction of the year covered by the enterprise agreement.

b. The values of work practice variables are constant until they are changed by the enterprise agreements that replace the old ones.

Table 3: Production function estimation Results. Dept Var=log(Saleable Coal Production)

					Robustness Check		
Variables	FE.1	M.LIK	OLS	2SLS	FE.2	FE.3	GMM
MultiBetween	0.29***	0.28***	0.32***	0.025	0.33**	0.31**	0.27***
	(0.1)	(0.006)	(0.1)	(0.28)	(0.14)	(0.13)	(0.05)
ClassRedu	0.017	0.017	0.049**	0.027	0.023	0.004	0.006
	(0.015)	(0.01)	(0.021)	(0.019)	(0.018)	(0.015)	(0.008)
Staff	0.14***	0.14***	0.14**	0.17***	0.03	0.16***	0.18***
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.04)	(0.03)
Product_Bonus	0.16***	0.16***	0.29***	0.11	0.05	0.18***	0.07*
	(0.05)	(0.03)	(0.09)	(0.08)	(0.12)	(0.04)	(0.04)
Continuity	0.014	0.015	-0.13**	0.04	0.008	0.014	-0.01
	(0.03)	(0.04)	(0.06)	(0.06)	(0.04)	(0.034)	(0.023)
No_Custom	-0.058	-0.057***	-0.11	-0.07	-0.07	-0.05	-0.04
	(0.08)	(0.01)	(0.1)	(0.07)	(0.09)	(0.08)	(0.05)
Advanced_bonus	-0.04	-0.04	-0.05	-0.008	-0.06	-0.05	-0.07
	(0.1)	(0.03)	(0.11)	(0.07)	(0.12)	(0.1)	(0.06)
Communication	0.07	0.07	-0.02	0.07	0.0004	0.03	0.12***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.068)	(0.04)	(0.04)
Monitoring	-0.05	-0.05***	-0.0004	-0.06	0.01	-0.02	0.04
	(0.09)	(0.02)	(0.08)	(0.06)	(0.08)	(0.09)	(0.05)
t	0.06	0.07***	0.13**	0.09	0.14**	0.11*	-0.21
	(0.05)	(0.03)	(0.06)	(0.10)	(0.065)	(0.05)	(0.39)
t^2	-0.002	-0.002	-0.006	-0.004	-0.01	-0.006	0.02
	(0.005)	(0.009)	(0.007)	(0.01)	(0.007)	(0.006)	(0.03)
$log(output)_{t-1}$							0.18***
							(0.04)
ρ_1		-2×10^{-18}					
		(2×10^{-15})					
ρ_2		-4×10^{-19}					
		(5×10^{-16})					
ρ_3		-3×10^{-18}					
		(10^{-17})					
R^2(within)	0.88		0.94	0.87	0.86	0.88	
# observations	288	288	288	288	167	253	240
H_0 Under-identified(p-val)				23.3 (0.003)			Arellano Bond test p-val =0.37
Hansen's J (p-val)				12.3 (0.09)			
H_0: multi-tasking exogeneous(p-val)				2.77 (0.25)			

The coefficients for all other variables are presented in Table 6. Underidentification test is based on Kleibergen-Paap (2006). Inside the parentheses are cluster robust standard for fixed effect specifications. Heteroschedasticity robust standard errors are reported for 2SLS and GMM. *Significant at 0.1, ** at 0.05, *** at 0.01.

Table 4: Effect of coal qualities on the adoption of multi-tasking

	Dept Var=MultiBetween			Dept Var=ClassRedu		
Variables	(Logit)	(OLS)	(Fixed effect)	(OLS)	(OLS)	(Fixed effect)
(SumImpurities)	11.00***			-0.37		
	(4.20)			(0.25)		
$(SumImpurities)^2$	-0.09***			0.003		
	(0.002)			(0.003)		
(Ash)		0.067**	0.04*		0.43**	0.18
		(0.03)	(0.024)		(0.17)	(0.18)
$(Ash)^2$		-0.0007	-0.0001		-0.007**	-0.006*
		(0.007)	(0.0006)		(0.004)	(0.003)
(VolatMatter)		-0.69***	0.02		0.87	-2.48***
		(0.13)	(0.13)		(0.57)	(0.82)
$(VolatMatter)^2$		0.012***	0.0001		-0.013	0.043***
		(0.002)	(0.002)		(0.009)	(0.014)
(Sulphur)		-0.59	-1.22**		0.93	19.81***
		(0.40)	(0.63)		(2.58)	(3.51)
$(Sulphur)^2$		0.34	0.53*		-2.25*	-11.39***
		(0.21)	(0.32)		(1.40)	(1.84)
(Moisture)		0.24***	0.22***		-0.88*	-0.69
		(0.08)	(0.08)		(0.46)	(0.50)
$(Moisture)^2$		-0.02***	-0.02***		0.063	0.04
		(0.007)	(0.007)		(0.40)	(0.043)
All other control vars except multi-tasking vars	No	Yes	Yes	Yes	Yes	Yes
R Squared	0.88	0.78	0.77	0.80	0.82	0.86
H_0: Coal qualities not joint significant (χ^2 or F, p-val)	10.9	7.75	3.44	1.23	5.90	6.99
	(0.00)	(0.00)	(0.00)	(0.29)	(0.00)	(0.00)
Shea' Partial R^2			0.08			0.22

a. Except for the logit model, all the variables treated as exogenous in the 2SLS estimation of production function (equation (1)) are included in the estimation. Thus, fixed effect results are identical to the first stage regressions of the 2SLS procedure.

b. The logit model excludes the cross products and the square terms of the input variables to avoid multi-collinearity.

c. (MultTask_Between) can take fraction (See footnote of Table 2). To discretize the variable, I transformed it as (MultTask_Between)=1 if it is greater than 0.5.

d. Insider parentheses are robust standard errors. *Significant at 0.1, **Significant at 0.05, ***Significant at 0.01

e. Test statistics for the null hypothesis are F-statistics except for Logit model where $\chi^2_{(2)}$ statistic is reported.

Table 5: Partial effects of coal qualities on the adoption of multi-tasking (based on the results in Table 4)

	Dept Var=MultiBetween			Dept Var=ClassRedu		
Models	(Logit) $\frac{\partial P}{\partial CoalQual}$	(OLS) $\frac{\partial Multi}{\partial CoalQual}$	(Fixed effect) $\frac{\partial Multi}{\partial CoalQual}$	(OLS) $\frac{\partial ClassRedu}{\partial CoalQual}$	(OLS) $\frac{\partial ClassRedu}{\partial CoalQual}$	(Fixed effect) $\frac{\partial ClassRedu}{\partial CoalQual}$
SumImpurities	0.035***			-0.001		
	(10.9)			(0.91)		
Ash		0.046***	0.042***		0.24**	0.02
		(7.25)	(6.66)		(3.41)	(1.83)
VolatMatter		0.13***	0.03**		0.004	0.36***
		(24.47)	(3.03)		(1.41)	(4.58)
Sulphur		-0.13	-0.47*		-2.54***	4.09***
		(1.23)	(2.63)		(19.78)	(19.77)
Moisture		0.10***	0.10**		-0.45**	-0.42***
		(5.39)	(4.42)		(4.39)	(4.99)

a. Inside the parentheses are the test statistics for the null hypothesis that the coefficients for the coal quality variable and its square are jointly equal to zero. They are F statistics, except for Logit model where chi square statistic is used. *Significant at 0.1, **Significant at 0.05, ***Significant at 0.01

b. Partial effects are computed at the sample average of each variable, except for the logit model. For the logit, the sample average of the partial effects is shown.

Table 6: Other coefficients on production function estimation

Variables	FE.1	M.LIK	OLS	2SLS	FE.2	FE.3	GMM
(JPN ownership)	1.07*	1.06***	-0.41	0.61	0.78	0.79*	0.74
	(0.59)	(0.02)	(0.43)	(0.53)	(1.09)	(0.43)	(0.48)
$(JPNownership)^2$	-0.57	0.57***	0.2	-0.25	-0.36	-0.46	-0.31
	(0.67)	(0.005)	(0.42)	(0.5)	(1.02)	(0.5)	(0.82)
(Oil Ownership)	-1.56	-1.55***	0.91**	-1.72	-0.053	0.26	-2.78***
	(1.03)	(0.006)	(0.37)	(0.75)	(1.87)	(0.43)	(0.58)
$(OilOwnership)^2$	1.8	1.8	-1.23***	1.85	0.05	-0.25	3.66***
	(1.14)	(0.004)	(0.4)	(0.85)	(1.68)	(0.45)	(0.75)
log(Employment)	4.07***	4.06***	1.45	4.07***	1.8	4.18***	4.29***
	(0.86)	(0.04)	(1.22)	(0.68)	(1.44)	(0.62)	(0.56)
log(Excavator)	-1.23*	-1.21***	0.86	-1.38*	-2.42*	-1.05	-0.94
	(0.7)	(0.02)	(1.36)	(0.82)	(1.35)	(0.66)	(0.78)
log(Bulldozer)	-1.30	-1.30***	-2.35	-0.93	0.14	-0.79	-0.63
	(1.2)	(0.007)	(1.46)	(1.01)	(1.69)	(1.18)	(0.82)
log(Truck)	-0.23	-0.24***	1.67	-0.31	1.45	-0.35	-0.88
	(0.66)	(0.04)	(1.04)	(0.62)	(1.11)	(0.68)	(0.6)
log(Thickness)	-0.18	-0.17***	0.05	-0.16	0.06	-0.17	-0.36***
	(0.15)	(0.04)	(0.078)	(0.15)	(0.18)	(0.16)	(0.1)
log(Employment)	-0.026	-0.025	0.24	0.04	0.51**	0.21	-0.14
×log(Excavator)	(0.16)	(0.14)	(0.18)	(0.16)	(0.21)	(0.1)	(0.11)
log(Employment)	-0.32*	-0.32	-0.09	-0.37***	-0.29	-0.45***	-0.32***
×log(Bulldozer)	(0.16)	(0.38)	(0.22)	(0.14)	(0.22)	(0.12)	(0.12)
log(Employment)	-0.16	-0.16	-0.05	-0.13	0.18	-0.24*	-0.26**
×log(Truck)	(0.15)	(0.12)	(0.14)	(0.14)	(0.25)	(0.13)	(0.11)
log(Excavator)	0.027	0.026	-0.60*	0.06	0.18	-0.01	0.19
×log(Bulldozer)	(0.18)	(0.12)	(0.31)	(0.2)	(0.28)	(0.2)	(0.15)
log(Excavator)	0.19	0.18	0.19	0.12	0.08	0.031	0.07
×log(Truck)	(0.21)	(0.30)	(0.19)	(0.18)	(0.2)	(0.17)	(0.2)
log(Bulldozer)	0.006	0.008	0.08	0.1	-0.05	0.08	0.18
×log(Truck)	(0.13)	(0.35)	(0.16)	(0.15)	(0.16)	(0.13)	(0.12)
$log(Employment)^2$	0.05	0.05	-0.07	0.04	-0.23*	0.08	0.15**
	(0.08)	(0.44)	(0.1)	(0.09)	(0.12)	(0.07)	(0.07)
$log(Excavator)^2$	-0.02	-0.02	0.15	-0.01	-0.25	-0.02	-0.03
	(0.12)	(0.15)	(0.19)	(0.12)	(0.18)	(0.13)	(0.09)
$log(Bulldozer)^2$	0.19	0.19	0.32*	0.13	0.07	0.18	0.008
	(0.13)	(0.13)	(0.17)	(0.12)	(0.17)	(0.15)	(0.12)
$log(Truck)^2$	0.01	-0.01	-0.19***	-0.02	-0.15	0.05	0.026
	(0.06)	(0.61)	(0.05)	(0.06)	(0.12)	(0.06)	(0.053)
Constant			1.06				
			(4.5)				

This table shows all other coefficients not shown in Table 3 except for year dummies.
Inside the parentheses are cluster robust standard errors except for 2SLS. *Significant at 0.1, ** at 0.05, *** at 0.01.

Appendix: The likelihood function

For notational simplicity, rewrite the equations (2), (3) and (4) respectively as

$$\begin{aligned}
Y_{1it} &= \alpha' X_{it} + (\varrho_1 \chi_i + e_{it}^{(1)}) && (5) \\
Y_{2it} &= \beta_1' X_{it} + \gamma_1' Z_{it} + (\varrho_2 \chi_i + e_{it}^{(2)}) && (6) \\
Y_{3it} &= \beta_2' X_{it} + \gamma_2' Z_{it} + (\varrho_3 \chi_i + e_{it}^{(3)}) && (7)
\end{aligned}$$

where all the variables are demeaned. X_{it} is the vector of all the regressors included in the production function. Z_{it} is the excluded instruments. We assume that $e_{it}^{(j)} \sim N(0, \sigma_{(j)}^2)$ for j=1,2, and 3, and assume that $\chi_i = N(0,1)$. The likelihood contribution of i^{th} mine conditional on χ_i is written as

$$\begin{aligned}
L_i(\Phi|\chi_i) &= \prod_t \phi(Y_{1it} - \alpha' X_{it} - \rho_1 \chi_i, \sigma_{(1)}^2) \\
&\times \phi(Y_{2it} - \beta_1' X_{it} - \gamma_1' Z_{it} - \rho_2 \chi_i, \sigma_{(2)}^2) && (8) \\
&\times \phi(Y_{3it} - \beta_2' X_{it} - \gamma_2' Z_{it} - \rho_3 \chi_i, \sigma_{(3)}^2)
\end{aligned}$$

where $\phi(\mu, \sigma^2)$ is a normal density function with mean μ and variance σ^2. To obtain the unconditional likelihood function, we integrate out χ_i by applying Gauss-Hermite approximation to normal integral with 25 mass points. This is written as

$$L_i(\Phi) \approx \sum_{k=1}^{25} w_k L_i(\Phi|v_k) \qquad (9)$$

where weights w_k and support v_k are computed by the Gauss-Hermite quadrature. The likelihood function is obtained by multiplying $L_i(\Phi)$ over all i.