# ABSTRACT

Title of dissertation: LABOR REALLOCATION, PRODUCTIVITY AND OUTPUT VOLATILITY IN JAPAN

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The dissertation offers an analysis of the labor reallocation process in Japan and sheds light on its relationship with productivity and output volatility during the 1990s, the period of sluggish growth. The first chapter provides descriptive statistics of job reallocation rates among relatively large Japanese firms. The main results show that job reallocation follows a steady decline in volatility between 1967 and 1997 and exhibits little deviation from its long-run trend in the 1990s. At the same time, the idiosyncratic effects of job reallocation appear to counteract the sectoral/aggregate effects during the 1990s in the manufacturing sector. Finally, the contribution of net entry to overall productivity growth has decreased during this period, mainly through exits by relatively productive firms.

The second chapter investigates the labor input and inventory responses to demand shocks in both the Japanese manufacturing sector as a whole, and the Iron and Steel industry. The main results show that first, demand shocks increased in volatility after 1992 in both the manufacturing sector and the Iron and Steel industry. Second, for the manufacturing sector, the adjustment mechanism shifted from an intensive use of inventories to more of a reliance on employment and work hours after 1992. Finally, for the Iron and Steel industry, the employment and inventory adjustments do not exhibit any systematic changes while the work hour adjustment has become more intense since 1992.

The third chapter provides a theoretical examination of the impact of the Employment Adjustment Subsidy (EAS). A partial equilibrium industry model with heterogeneous establishments and aggregate uncertainty shows that the EAS lowers labor productivity, while reducing job flows

and increasing average firm-level employment. While the directly measured impact on productivity is proportional to the fraction of subsidized workers, the indirect effects of the subsidy on output and employment volatility can be substantially larger. The subsidy can lead to a sizable increase in output fluctuations over the business cycle by symmetrically increasing the output response to shocks, while still meeting its primary objective of reduced employment volatility.

# LABOR REALLOCATION, PRODUCTIVITY AND OUTPUT VOLATILITY IN JAPAN

by

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# FOREWORD

Chapter 1 of the dissertation, entitled "Evaluation of the Reallocation Mechanism during the 'Lost Decade' of the 1990s," represents joint work between Naomi Griffin and Kazuhiko Odaki at the Financial Services Agency of the Japanese government. Naomi's examining committee has determined that she has made a substantial contribution to this joint work. This work is included in this thesis with the approval of Prof. John Haltiwanger, the chair of Naomi's dissertation committee, and of Prof. John Shea, a member of Naomi's committee and the Director of Graduate Studies for the Department of Economics.

This dissertation is dedicated to Ed.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

# Chapter 1

# Evaluation of the Reallocation Mechanism during the 'Lost Decade' of the 1990s

## 1.1 Introduction

This chapter provides descriptive statistics that highlight the labor reallocation mechanism, a critical component for understanding the business cycle, in Japan. In particular, we use a firm level dataset (the Nikkei financial dataset) to investigate the annual rates of job creation and destruction between 1965 and 1997 among relatively large, publicly traded firms. The primary interest of this exercise is to investigate the characteristics of job reallocation during the 1990s, a period of sluggish economic growth, relative to other periods. In addition, we conduct productivity decomposition exercises to examine if the cleansing effect of recessions (i.e. downsizing/exit of the least productive firms) was in place during the first half of the 1990s. The main results show that job reallocation, the sum of job creation and job destruction, follows a steady decline in volatility between 1967 and 1997. We conjecture that this is associated with a decline in the trend employment growth rate, as job reallocation dynamics in Japan are mainly creation driven. Whereas the job reallocation rate exhibited little deviation from its long-run trend in the 1990s, we observe that the dominance of the idiosyncratic component relative to the sectoral/aggregate component in explaining overall reallocation dynamics declines during the 1990s in the manufacturing sector. The idiosyncratic effects also appear to counterbalance the sectoral/aggregate effects during this period. Finally, the productivity decomposition exercises reveal that the contribution of net entry to overall productivity growth has decreased in recent years. In particular, exit by relatively productive firms constitute this reduction in the contribution of net entry.

The 1990s marked the first decade of sluggish economic growth for the Japanese economy since the end of the Second World War. The deterioration of Japan's economic performance, which persisted over a decade, has interested many macroeconomists, yet not enough evidence has been unmasked to generate a consensus regarding the factors that have contributed to the lengthy recovery. The early stage of the preceding discussion centered around policy failures in the area of demand management, notably highlighted by a "liquidity trap" hypothesis or "credit crunch" problem. However, formal evidence in support of these hypothesis has not yet been found.

The proponents of the "liquidity trap" hypothesis claim that the monetary authority's inability to stimulate investment by lowering interest rates, or consumer spending by creating inflationary expectations, unnecessarily prolonged the recovery phase. On the other hand, the "credit crunch" hypothesis speculates that the poor financial condition among many Japanese banks was leading to the banks' reduced lending to profitable projects, thereby contributing to lower investment. However, Motonishi and Yoshikawa (1999), using the Bank of Japan diffusion indices of "real profitability" and "banks' willingness to lend," find that except for 1997 when the government finally allowed some big banks to fail, drops in investment were unrelated to banks' willingness to lend and were mainly driven by a fall in real profitability.[1] Furthermore, using growth accounting, Hayashi and Prescott (2002) argue that the economic stagnation during the 1990s in Japan is largely explained by a fall in exogenous TFP growth.

More recent literature identifies the reallocation issue as the primary problem. For example, Peek and Rosengren (2003) find the evidence of misallocation of credit by Japanese banks as they engaged in "evergreening" loans. Namely, they claim that financially troubled firms were more likely to obtain further loans from banks than their healthier counterparts during the 1990s, as banks sought to manipulate their balance sheets by making financially troubled firms look artificially solvent. Likewise, using stock returns, Hamao, Mei and Xu (2003) suggest that there was a lack of resource reallocation in Japan during the 1990s. In particular, when a firm's idiosyncratic risk is measured as the deviation of its stock return from the average response to the market rate, they show that the role of idiosyncratic risk in explaining the total time-series volatility of firm stock returns decreased during the 1990s. Consequently, they point out that this apparent increase in homogeneity of corporate performance may have hindered the ability of

[1] Woo (1999) finds similar results.

investors and managers to distinguish high quality firms from low quality firms, and discouraged capital formation.

These findings indicate that misallocation, or the lack of reallocation, may provide us with a better understanding of the problem. In fact, a considerable amount of research relates reallocation to economic performance and growth over the business cycle. The theoretical aspects of the literature often focus on Schumpeter's idea of "creative destruction." Aghion and Howitt (1992), for instance, construct an endogenous growth model in which old technology is immediately destroyed with the emergence of new technology, thereby constituting the underlying engine of economic growth through the introduction of a competitive research sector that generates vertical innovations. In a similar spirit, Caballero and Hammour (1994, 1996) created a model in which only entering firms have access to the latest vintage of capital, and therefore the destruction of firms with old vintages facilitates the flow of new entries and is productivity enhancing.

On the empirical front, Davis and Haltiwanger (1992) and Davis, Haltiwanger and Schuh (1996) have demonstrated, using a longitudinal plant level dataset from the US manufacturing sector, that recessions are associated with volatile job reallocation as a result of excessive job destruction compared to job creation, and much of the variation in job reallocation is explained by the idiosyncratic component. Consequently, the empirical study in this chapter looks at the reallocation aspect of Japanese firms' performance during the recessionary years. In particular, we highlight the job reallocation process among relatively large, publicly traded firms.[2]

The Nikkei financial dataset between 1964 and 1997 shows that the variation in the job reallocation rate has been declining during this period. This is because job creation plays the largest role in driving job reallocation dynamics in Japan, and variation in job creation declined over time as the trend employment growth rate declined. Moreover, we do not observe any obvious changes to the declining trend of job reallocation during the 1990s. While there is a mild increase

[2] The studies on the characteristics of job reallocation in Japan are limited primarily due to a lack of a dataset as comprehensive as the Longitudinal Research Database used by Davis and Haltiwanger (1992), and as a result, an in-depth cross-country comparison with the facts on the reallocation activities of the U.S. manufacturing sector has not yet been possible.

in the job destruction rate during the 1990s, it was offset by a reduction in the job creation rate of a similar magnitude. As a result, in contrast to what one might expect given evidence from the US manufacturing sector, the dramatic and persistent reduction in the growth rate which started in 1992 was not accompanied by a sudden rise in the job reallocation rate. These results are observed in both the manufacturing and the non-manufacturing sector, but relatively speaking, the role of job destruction is even smaller in the non-manufacturing sector when compared to the manufacturing sector.

The general finding is consistent with a study done by Genda (1998), which computes job creation and destruction rates during the five-year interval between 1991 and 1995 for continuing establishments from the *Employment Trend Survey*.[3] He emphasizes the relatively large role played by job creation in driving reallocation dynamics during this period of economic downturn, thereby highlighting potential differences in the labor adjustment mechanism between the U.S. and Japan in response to negative shocks.[4]

While we do not observe any major change in the long-run trend of the variation in the job reallocation rate during the 1990s, the characteristics of the components comprising job reallocation changed dramatically during the 1990s in the manufacturing sector. More specifically, we decompose job reallocation rates into an idiosyncratic component and a sectoral/aggregate component in order to examine the relative importance of these two components in explaining the overall variation of job reallocation. The results show that, in the manufacturing sector, the relative dominance of the idiosyncratic component over the sectoral/aggregate component declined in the 1987−1997 period. This result is similar to the finding by Hamao, Mei and Xu (2003) that heterogeneity in corporate performance as measured by stock returns declined during the 1990s. Furthermore, the correlation between the idiosyncratic and the sectoral/aggregate compo-

[3]The approximate number of sample establishments of the survey used in Genda (1997) varies from 10,000 to 12,000 each year.

[4]Although Foote (1998) shows that the relative importance of job destruction as opposed to job creation in driving cyclical dynamics can depend on employment trend growth, it seems that the difference in trend growth rates alone cannot explain the low job reallocation in Japan during the 1990s.

nent was significantly negative in the period 1987−1997. Similar changes were not observed in the non-manufacturing sector.

Finally, we conduct productivity decomposition exercises to examine whether or not the cleansing effect of recessions was taking place via downsizing and exits by inefficient firms. Foster, Haltiwanger and Krizan (1998) show that, in the US manufacturing sector, the contribution of reallocation in explaining aggregate productivity growth through the replacement of relatively inefficient establishments by more productive ones is significant, and entry/exit dynamics play an important role. Similar exercises done for Japanese manufacturing firms using the Nikkei financial dataset show that while some downsizing of inefficient firms took place and contributed to overall productivity growth between 1988 and 1997, the contribution of net entry is weak during this period. In particular, the TFP growth decomposition shows that exit of inefficient firms is not observed during this period. Thus, the overall results indicate rather slow reallocation dynamics among large Japanese firms during the 1990s prior to 1997. The observed lack of exit among the least efficient firms match the finding by Peek and Rosengren (2003) that banks deliberately helped financially troubled firms to stay in business.

## 1.2 Description of the Dataset

The main dataset used in this chapter is the Nikkei financial dataset from 1964 to 1998. It contains about 2500 relatively large nonfinancial firms, and the primary advantage of the dataset is that it allows us to examine changes in reallocation dynamics over time. Firms included are those that are listed on the Tokyo Stock Exchange, JASDAQ and other regional stock markets, leading unlisted companies submitting financial reports to the Ministry of Finance, and other leading unlisted companies that are not included in the above mentioned categories but submit reports to their shareholders. The dataset has financial as well as employment data, with some corporate information.

The dataset is an unbalanced panel, in which 70% of the 78,670 observations are based on annual reports while the remainder are mostly based on semi-annual reports. The number of firms covered in the dataset increases over time, as the number of entries into the dataset are much larger than the number of exits from the dataset. There are two unusually large flows of entries into the dataset in 1965 and 1970. The increase in 1965 is likely to be associated with part of the initial data collection process, while the increase in 1970 is related to the inclusion of firms listed on other stock markets.[5] Firms in the dataset are classified according to their Nikkei industry classification, which does not always clearly match the standard government classification. Industry categories excluded in this dataset are banks, investment banks, and insurance companies.[6]

Table (1.1) provides descriptive statistics of firm level employment in the Nikkei financial dataset. Note that the figures correspond to the average of the annual statistics in each time interval. Also, the annual average employment figure is used for firms which submit reports semi-annually. The top part of the table gives descriptive statistics of the entire dataset. As we can see, the average firm size in terms of employment falls while the average number of firms increases over time, most likely reflecting the incorporation of smaller size firms, or the spin off of divisions into separate business entities.

The middle part of the table gives the descriptive statistics of firm level employment for entering firms only. Note that entry into the dataset does not necessarily imply entry into the market, but rather has more to do with being listed on a stock exchange. The privatization of Nippon Telegraph and Telephone (NTT) in 1986 as well as Japan Railway (JR) in 1988 generate a significant jump in the average size and standard deviation of entering firms for the period 1985−1989. The bottom part of the table identifies statistics for firms that dropped from the dataset. Again, dropping from the dataset does not necessarily mean exit from the market, as it could imply either bankruptcy, merger, or restructuring as a private entity. Compared to the number of entering firms, the average number of firms that exit from the dataset is relatively

[5] Only firms listed on the Tokyo Stock Exchange (TSE) were included in 1964. Firms listed on Osaka and Nagoya stock exchanges were incorporated in 1970, other listed firms from smaller regional stock markets were incorporated in 1975, and leading unlisted companies submitting financial report to the Ministry of Finance or reports to their shareholders were added in 1977.

[6] 131 out of 140 three-digit industries and 32 out of 36 two-digit industries, according to their Nikkei classification, are included in the dataset.

Table 1.1: Descriptive statistics of firm level employment in the Nikkei financial dataset for 1965−1997, for all firms, entering firms and exiting firms.

| Period | Mean | Average median | Average standard deviation | Average minimum | Average maximum | Average number of firms |
|---|---|---|---|---|---|---|
| | | | A. Entire dataset | | | |
| 1965−1969 | 2616 | 1051 | 5675 | 24 | 80870 | 1406 |
| 1970−1974 | 2590 | 1018 | 6017 | 24 | 86566 | 1696 |
| 1975−1979 | 2333 | 888 | 5486 | 10 | 77344 | 1853 |
| 1980−1984 | 2116 | 801 | 5031 | 12 | 73732 | 2042 |
| 1985−1989 | 2173 | 773 | 7423 | 7 | 249295 | 2195 |
| 1990−1997 | 2220 | 812 | 6992 | 6 | 223009 | 2344 |
| | | | B. Entering firms | | | |
| 1965−1969 | 665 | 394 | 790 | 48 | 3503 | 41 |
| 1970−1974 | 1181 | 456 | 1969 | 85 | 7256 | 66 |
| 1975−1979 | 662 | 439 | 864 | 33 | 6381 | 58 |
| 1980−1984 | 502 | 341 | 506 | 43 | 2323 | 34 |
| 1985−1989 | 3052 | 261 | 13429 | 25 | 79276 | 38 |
| 1990−1997 | 657 | 472 | 613 | 194 | 1822 | 18 |
| | | | C. Exiting firms | | | |
| 1965−1969 | 5167 | 4773 | 3806 | 2752 | 8348 | 3 |
| 1970−1974 | 1809 | 951 | 2800 | 196 | 8651 | 7 |
| 1975−1979 | 786 | 399 | 796 | 181 | 2174 | 6 |
| 1980−1984 | 709 | 537 | 843 | 58 | 2291 | 7 |
| 1985−1989 | 1100 | 500 | 1672 | 93 | 4297 | 5 |
| 1990−1997 | 1094 | 800 | 1089 | 294 | 2978 | 6 |

small.

Since entries and exits into the dataset may not be related to the state of the economy, employment growth rates constructed with the Nikkei dataset with and without entries/exits are compared with the employment growth rates given by the Labor Force Survey, which includes employment for the entire economy.[7] The correlation between the two is 0.5089 when all entering and exiting firms are excluded from the calculation, and falls to 0.4742 when they are included. There are exceptionally large flow of entries in 1965, 1970, 1977 and 1978. Moreover, the privati-

[7]The time series employment data from Labor Force Survey is available at the following website: http://www.stat.go.jp/data/roudou/longtime/03roudou.htm. Total employment growth is constructed using the 'total number of employees' from Table 1.

zation of NTT in 1986 and JR in 1988 affects the employment growth rate of the Nikkei dataset significantly. When those entries are excluded from the computation while including other entries/exits, the correlation goes up slightly to 0.5053. Therefore, we will employ this adjustment with entries and exits incorporated for our analysis of job reallocation.

Finally, out of 2531 firms with employment data, approximately 59% belong to 'Manufacturing', 16% to 'Wholesale, Retail Trade, Eating and Drinking Places', 8% to 'Construction', 5.5% to 'Transport and Communication', 6.5% to 'Service', and 3.5% to 'Financing, Insurance and Real Estate'.[8] The examination of firm level job reallocation will be executed for both the manufacturing sector (1487 firms) and the non-manufacturing sector (1044 firms). Productivity decomposition exercises are only done for the manufacturing sector, however, since the sectoral deflators provided by the Bank of Japan (CGPI) are available only for manufacturing industries.

## 1.3 Job Reallocation

The annual job creation, job destruction and job reallocation rates are constructed following Davis and Haltiwanger (1992) and Davis, Haltiwanger and Schuh (1996):

$$JC_t = \sum_{i,g_{it>0}}^{I_t} (\overline{E}_{it}/\overline{E}_t) g_{it}, \quad JD_t = \sum_{i,g_{it<0}}^{I_t} (\overline{E}_{it}/\overline{E}_t) g_{it}, \quad \text{and} \quad JR_t = JC_t + JD_t \tag{1.1}$$

where $I_t$ is the total number of firms at time $t$, $g_{it} = (E_{it} - E_{it-1}) / \overline{E}_{it}$, $\overline{E}_{it} = (E_{it} + E_{it-1}) / 2$ and $E_{it}$ is employment of firm $i$ at year $t$. Also note that the average figures of employment for each year are used for firms that submit reports semi-annually.

Figure (1.1) and figure (1.2) show the percentage rates of job creation and job destruction for firms in the manufacturing and non-manufacturing sectors between 1965 and 1997.[9] Both figures show a larger share of variability arising from job creation before the mid-1970s. Job destruction is particularly stable relative to job creation in the non-manufacturing sector. The larger role of job creation in driving job reallocation dynamics in this sector may be attributed to

[8] There are also very small number of firms which belong to 'Fisheries', 'Mining', and 'Electricity, Gas, Heat and Water Supply'.

[9] Note that observations from the first year (1964) and the last year (1998) of the dataset are not used for the analysis as the data appears to be incomplete in these years.

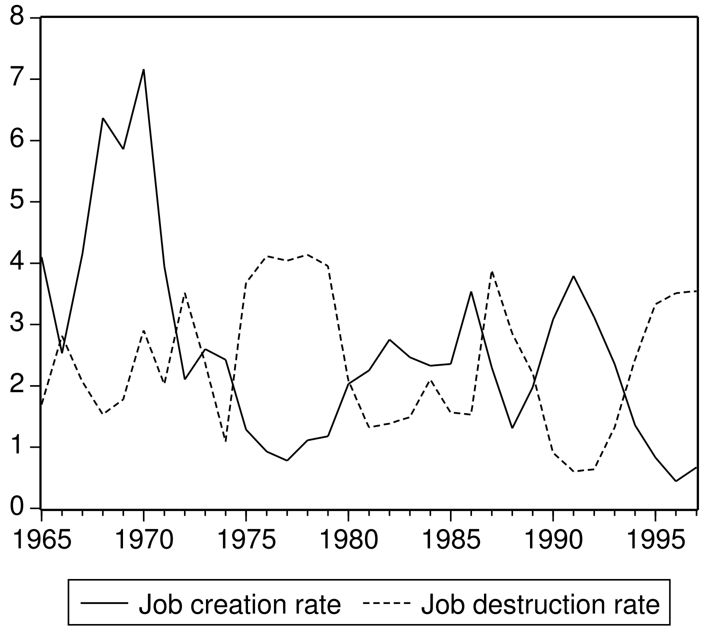


Figure 1.1: Annual job creation and job destruction rate (in percentage) in the manufacturing sector calculated using the Nikkei financial dataset for 1965−1997.

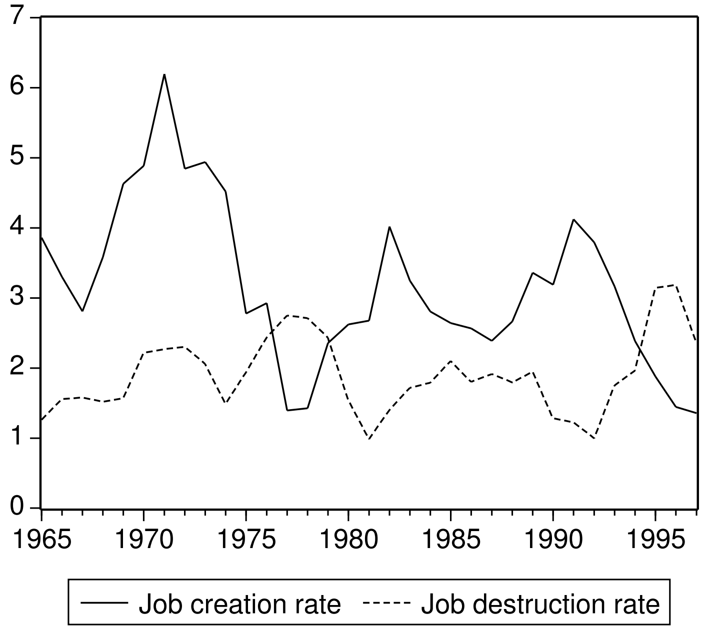


Figure 1.2: Annual job creation and job destruction rate (in percentage) in the non-manufacturing sector calculated using the Nikkei financial dataset for 1965−1997.

the sectoral employment trend growth rate which is higher in the non-manufacturing sector than the manufacturing sector, as described by Foote (1988).

Table 1.2: Correlation matrix of the various measures of job reallocation in the manufacturing sector for 1965−1997.

| | $JC_t$ | $JD_t$ | $JR_t$ | $\widetilde{JR}_t$ | $JR_t - \widetilde{JR}_t$ | $JC_t - JD_t$ |
|---|---|---|---|---|---|---|
| $JC_t$ | 1.000 | | | | | |
| $JD_t$ | -0.506 | 1.000 | | | | |
| $JR_t$ | 0.747 | 0.195 | 1.000 | | | |
| $\widetilde{JR}_t$ | 0.735 | 0.142 | 0.945 | 1.000 | | |
| $JR_t - \widetilde{JR}_t$ | 0.456 | 0.229 | 0.695 | 0.423 | 1.000 | |
| $JC_t - JD_t$ | 0.917 | -0.808 | 0.420 | 0.436 | 0.206 | 1.000 |

Table 1.3: Correlation matrix of the various measures of job reallocation in the non-manufacturing sector for 1965−1997.

| | $JC_t$ | $JD_t$ | $JR_t$ | $\widetilde{JR}_t$ | $JR_t - \widetilde{JR}_t$ | $JC_t - JD_t$ |
|---|---|---|---|---|---|---|
| $JC_t$ | 1.000 | | | | | |
| $JD_t$ | -0.397 | 1.000 | | | | |
| $JR_t$ | 0.878 | 0.091 | 1.000 | | | |
| $\widetilde{JR}_t$ | 0.741 | 0.128 | 0.871 | 1.000 | | |
| $JR_t - \widetilde{JR}_t$ | 0.569 | -0.026 | 0.604 | 0.135 | 1.000 | |
| $JC_t - JD_t$ | 0.938 | -0.691 | 0.658 | 0.536 | 0.458 | 1.000 |

Table (1.2) and (1.3) show the correlation matrix of the various measures of job reallocation in the manufacturing and the non-manufacturing sector, respectively, between 1965 and 1997. As expected, $JR_t$ has a higher correlation with $JC_t$ than $JD_t$, and this pattern is much stronger for the non-manufacturing sector. $JC_t$ and $JD_t$ are negatively correlated, but the correlation is stronger for the manufacturing sector. Furthermore, as a result of higher volatility in job creation, job reallocation (i.e. $JC_t + JD_t$) and net job creation (i.e. $JC_t - JD_t$) are positively correlated: the correlation is 0.42 for the manufacturing sector and 0.66 for the non-manufacturing sector. As mentioned earlier, this evidence is consistent with Genda (1997) for continuing establishments between 1991 and 1995, while it stands in contrast with the evidence from the U.S. manufacturing sector that job destruction is more volatile than job creation and that, therefore, job reallocation moves countercyclically.[10]

Next, following Davis and Haltiwanger (1990, 1992), the job reallocation rate, which is the sum of the job creation and destruction rates, is decomposed into a sectoral/aggregate component and an idiosyncratic component to examine their relative importance in driving the time variation of job reallocation. Let $g_{it,i\in j}$ be the employment growth rate of firm $i$ in industry $j$ at time $t$, and decompose it in a linear fashion as $g_{it,i\in j} = \widetilde{g}_{it} + g_{jt}$, where $g_{jt}$ is the employment growth rate of sector $j$, and $\widetilde{g}_{it}$ is the residual idiosyncratic component. The idiosyncratic component of job reallocation is given by

$$\widetilde{JR}_t = \sum_{i}^{I_t} (\overline{E}_{it}/\overline{E}_t) \mid \widetilde{g}_{it} \mid . \tag{1.2}$$

The sectoral/aggregate component of job reallocation is $JR_t - \widetilde{JR}_t$. The correlation matrix table shows that, both for manufacturing and non-manufacturing, the correlation of job reallocation is higher with the idiosyncratic component than the sectoral/aggregate component for the entire sample period.

Furthermore, using the identity $JR_t = \widetilde{JR}_t + (JR_t - \widetilde{JR}_t)$, the variance of job reallocation is decomposed as follows:

$$var(JR_t) = var(\widetilde{JR}_t) + var(JR_t - \widetilde{JR}_t) + 2cov(\widetilde{JR}_t, JR_t - \widetilde{JR}_t) \tag{1.3}$$

This decomposition allows us to identify the fraction of variation in job reallocation arising from the variation in the idiosyncratic and sectoral/aggregate components, while controlling for the covariance between the two. Table (1.4) gives the results for the variance decomposition exercise for both the manufacturing and non-manufacturing sectors. The sample period is divided into three

[10] Also, Motonishi and Tachibanaki (1999) use establishment level data for 1988, 1990 and 1993 from "Census of Manufacturers," which includes all establishments with more than four employees constructed by the Ministry of International Trade and Industry, to calculate job creation and destruction rates and they find that, during this period of economic downturn, the reduction in job creation rate is more dramatic than the increase in the job destruction rate. Job creation (destruction) rate is 6.16% (5.3%) for 1988−1990 and 4.23% (5.59%) for 1990−1993.

Table 1.4: Variance decomposition results for the manufacturing and the non-manufacturing sector for 1967−1997, based on two-digit and three-digit Nikkei industry classifications.

| | Manufacturing | | | Non-manufacturing | | |
|---|---|---|---|---|---|---|
| | 1967−1977 | 1977−1987 | 1987−1997 | 1967−1977 | 1977−1987 | 1987−1997 |
| **3-digit classification** | | | | | | |
| $Var(JR_t)$ | 3.984 | 0.370 | 0.057 | 1.429 | 0.269 | 0.134 |
| Fraction of variance accounted for by | | | | | | |
| –Idiosyncratic effects | 0.516 | 0.663 | 2.203 | 0.421 | 1.650 | 1.199 |
| –Sectoral/aggegate mean effects | 0.110 | 0.314 | 2.683 | 0.393 | 0.131 | 0.483 |
| –Covariance effects | 0.373 | 0.022 | -3.886 | 0.186 | -0.781 | -0.682 |
| **2-digit classification** | | | | | | |
| $Var(JR_t)$ | 3.984 | 0.370 | 0.057 | 1.429 | 0.269 | 0.134 |
| Fraction of variance accounted for by | | | | | | |
| –Idiosyncratic effects | 0.514 | 0.885 | 2.723 | 0.597 | 1.289 | 1.289 |
| –Sectoral/aggegate mean effects | 0.112 | 0.317 | 2.668 | 0.186 | 0.093 | 0.539 |
| –Covariance effects | 0.374 | -0.203 | -4.391 | 0.217 | -0.382 | -0.827 |

sub-periods to track the change over time: 1967−1977, 1977−1987 and 1987−1997. Furthermore, the sectoral growth rate, $g_{jt}$, is measured both at the three-digit and two-digit level of the Nikkei industry classification. The results are similar for both the two- and three-digit classifications. First, notice that the variance of the job reallocation rate declines over time. As mentioned previously, this most likely relates to the decline in the trend growth rate over time, since job reallocation in Japan has mostly been creation-driven.

The manufacturing sector experiences a significant change in the 1987−1997 period. Prior to this, the idiosyncratic component played a dominant role in the overall variation in job reallocation. However, the 1987−1997 period is characterized by a smaller and equally significant role for the idiosyncratic component respectively, for the three-digit and the two-digit classification. More interestingly, the covariance between the idiosyncratic and the sectoral/aggregate components became considerably negative during this period. The correlation between the two is $-0.80$ for the three-digit case and $-0.81$ for the two-digit case, statistically significant at the 1% level in both cases. On the contrary, we do not observe any dramatic change for the non-manufacturing sector during the 1987−1997 period. The relative dominance of idiosyncratic effects continues, and unlike the manufacturing sector, the correlation between the idiosyncratic and sectoral/aggregate effects is negative in all cases after 1977 as shown by the covariance terms. However, most of them are statistically insignificant at the 10% level.[11]

The decline in the relative dominance of the idiosyncratic component in the manufacturing sector seems consistent with the finding by Hamao, Mei and Xu (2003) that the heterogeneity of corporate performance measured in terms of idiosyncratic risks decreased during the 1990s, or put differently, the aggregate market return has become increasingly important relative to idiosyncratic risks in assessing firms' stock returns. However, a similar change was not observed in the non-manufacturing sector. The negative covariance term indicates that higher sectoral/aggregate disturbances were associated with smaller idiosyncratic reallocation activity. Accordingly, the idiosyncratic effects appear to "counteract the impact of aggregate and sectoral effects" on job reallocation particularly in the manufacturing sector during the 1987−1997 period.[12] It will be interesting to investigate the sources which resulted in this change, but this particular agenda is merely noted here as a topic of future research.

## 1.4 Productivity Decomposition

Using plant level data from the Census of Manufactures, Foster, Krizan and Haltiwanger (1998) show that reallocation of outputs and inputs across establishments as well as reallocation through entry and exit play an important role in explaining aggregate productivity growth. In this section, we conduct similar productivity decomposition exercises using the Nikkei financial dataset in order to explain productivity dynamics among relatively large Japanese firms.

Two types of decomposition exercises, following Foster, Krizan and Haltiwanger (1998), are conducted. Denoting $\Delta P_{jt}$ as the productivity growth of industry $j$ between $t-1$ (beginning

[11] The only decomposition with statistically significant correlation between the idiosyncratic and sectoral/aggregate effects is the three-digit level case for the 1977−1987 period. The correlation is 0.84.

[12] Davis and Haltiwanger (1992), p.853.

period) and $t$ (ending period), the first decomposition is given by the following equation:

$$\Delta P_{jt} = \sum_{i\in C} s_{it-1}\Delta p_{it} + \sum_{i\in C}(p_{it-1} - P_{jt-1})\Delta s_{it} + \sum_{i\in C}\Delta s_{it}\Delta p_{it} \\ + \sum_{i\in N} s_{it}(p_{it} - P_{jt-1}) - \sum_{i\in X} s_{it-1}(p_{it-1} - P_{jt-1}) \tag{1.4}$$

where $s_i$ is the share of firm $i$ in industry $j$, $p_i$ and $P_j$ are the indices of productivity for firm and industry respectively, and $C$, $N$ and $X$ indicate the set of continuing firms, entering firms and exiting firms respectively. The second decomposition is given by

$$\Delta P_{jt} = \sum_{i\in C} \overline{s}_{it}\Delta p_{it} + \sum_{i\in C}(\overline{p}_{it} - \overline{P}_{jt})\Delta s_{it} \\ + \sum_{i\in N} s_{it}(p_{it} - \overline{P}_{jt}) - \sum_{i\in X} s_{it-1}(p_{it-1} - \overline{P}_{jt}) \tag{1.5}$$

where a bar over a variable indicates the value averaged over $t-1$ and $t$.

The first term in both equation 1.4 and 1.5 shows contribution of the 'within' firm productivity growth to aggregate productivity growth. On the other hand, the second term shows the contribution arising from reshuffling of inputs or outputs across firms, or the 'between' firm effect. Here, the changes in shares are weighted in both cases by the deviation of firm productivity from the corresponding industry productivity index. The index in the first decomposition uses beginning period industry productivity, $P_{jt-1}$, while the second decomposition uses industry productivity averaged over the beginning and ending period. The last two terms represent the contribution of entry and exit respectively. Note that a firm's entry into the dataset raises aggregate productivity when its productivity is above the industry productivity index. Likewise, a firm's exit from the dataset raises aggregate productivity when its productivity is below the industry productivity index.

As we can see, the share weight used for the 'within' effect and the productivity weight used for the 'between' effect in the second decomposition given by equation 1.5 are average figures and therefore, the interaction effect between changes in share and changes in productivity is already incorporated in the first two terms, while the first decomposition given by equation 1.4 explicitly controls for this effect with the third 'cross' term. While the first method provides a more accurate decomposition, it is more sensitive to measurement errors as discussed in Foster, Krizan and Haltiwanger (1998), and therefore, the results using both decomposition methods will be presented.[13]

Two types of productivity measures, labor productivity and total factor productivity (TFP), are constructed for the decomposition exercises. Since the Nikkei dataset does not have information on manhours, the labor productivity measure used here is the log difference of real gross output and employment. Note that the real gross output figures were summed over each year when firms submit reports more than once a year, while the average employment figures are used for these firms. Furthermore, since the industry level price indices used to deflate gross output and materials were available only for the industries within manufacturing, the decomposition exercises are restricted to the manufacturing sector.

The index of TFP is measured simply as follows:

$$\ln TFP_{it} = \ln Y_{it} - \alpha_M \ln M_{it} - \alpha_L \ln L_{it} - (1 - \alpha_M - \alpha_L) \ln K_{it} \tag{1.6}$$

where $Y_{it}$ is real gross output for firm $i$ at year $t$, $M_{it}$ is real materials, $L_{it}$ is employment, $K_{it}$ is the real capital stock, $\alpha_M$ is material's share of total cost, and $\alpha_L$ is labor's share of total cost.[14] Detailed explanations of the construction of real gross output, real materials, and real capital stock using the Nikkei financial dataset are provided in the appendix.

Note that the notations for the material cost share $\alpha_M$ and the labor cost share $\alpha_L$ are simplified here, as the shares actually used vary across three-digit Nikkei industry classifications, although not over time. The material and labor cost shares are first calculated at the firm level by a taking simple average across time, and are then aggregated at the industry level using the firm level mean employment as a weight. When aggregated across all firms in the dataset, the

[13]For instance, a measurement error in labor input generates spuriously high negative correlation between the change in share and labor productivity growth. This, in turn, raises the 'within' effect. Similarly, a measurement error in output, in the case of conducting decomposition with TFP for instance, generates a spuriously high positive correlation between the change in share and TFP growth. This reduces the 'within' effect. Since the second method uses the average figures, it is less sensitive to this type of measurement error.

[14]Again, material input values are summed over a year for firms which submit reports more than once a year.

material cost share is 67.5%, while the labor cost share is about 16.1% and the capital cost share is about 16.4%.

The time horizon over which we investigate productivity growth is set between 8 to 10 years. This time horizon indicates the distance between the subscript $t$ and the subscript $t-1$ in equations 1.4 and 1.5. Accordingly, the analysis decomposes productivity growth dynamics over the long-run. Ideally, the starting period and the ending period should encompass the full business cycle. This allows us to compare the results across different time periods while avoiding short-run business cycle effects on productivity. Hence, we divided the entire productivity series into three sub-periods based on the following business cycle considerations: 1) a high growth period (from the peak of 1969 to the peak of 1979), 2) the bubble economy period (from the peak of 1979 to the peak of 1988) and 3) the sluggish growth period (from the peak of 1988 to the peak of 1996).

Table (1.5) shows the results of productivity decompositions using labor productivity and TFP. The measure of the share ($s_{it}$) used for labor productivity is employment, while that used for TFP is real gross output. The top part of the table shows the results using the first decomposition method and the bottom part of the table shows the results using the second decomposition method.

To begin with, the first column shows that the 'within' component explains almost all the productivity growth, except for TFP growth during the period of sluggish growth. The signs of the 'between' effect for labor productivity are not consistent across time periods. A negative 'between' implies that firms with labor productivity below the industry average expanded more in terms of employment. This result is not necessarily puzzling if, among the firms in the dataset, high productivity sites characteristically increased in capital intensity over time while reducing employment. Accordingly, the expansion for these firms may have been taking place through capital deepening instead of employment, with an increase in capital-labor ratio. Since the negative 'cross' term implies a negative correlation between labor productivity growth and employment growth, this may also be capturing the effect of increased capital intensity at the high productivity sites. This can also take place via an increase in TFP among downsizing firms.

Since the effect of capital accumulation on output is taken into account in the calculation

Table 1.5: Productivity decomposition results for the manufacturing sector using labor productivity and TFP for 1969−1996.

| | Within | Between | Cross | Entry | Exit | (Net entry) | Overall | Num. of firms |
|---|---|---|---|---|---|---|---|---|
| A. Decomposition 1 | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (4)-(5) | growth | (entries/exits) |
| LP | | | | | | | | |
| 1969−1979 | 71.8% | 4.1% | -7.1% | 4.2% | 1.2% | 3.1% | 71.8% | 1274 (312/43) |
| 1979−1988 | 51.5% | -2.1% | -1.0% | 2.3% | 0.3% | 2.0% | 50.4% | 1346 (115/43) |
| 1988−1996 | 30.9% | 1.2% | -2.7% | 0.0% | 0.4% | -0.3% | 29.1% | 1360 (57/22) |
| TFP | | | | | | | | |
| 1969−1979 | 15.1% | -7.1% | 0.4% | 1.8% | -0.7% | 2.5% | 10.8% | 1148(263/41) |
| 1979−1988 | 13.0% | -3.6% | -0.3% | 0.5% | -0.7% | 1.1% | 10.2% | 1262 (91/42) |
| 1988−1996 | 4.6% | -0.5% | 2.2% | 0.5% | 0.4% | 0.1% | 6.4% | 1304 (55/21) |
| B. Decomposition 2 | | | | | | | | |
| | Within | Between | Cross | Entry | Exit | (Net entry) | Overall | Num. of firms |
| | (1) | (2) | (3) | (4) | (5) | (4)-(5) | growth | (entries/exits) |
| LP | | | | | | | | |
| 1969−1979 | 68.2% | 2.2% | | 1.6% | 0.1% | 1.5% | 71.8% | 1274 (312/43) |
| 1979−1988 | 51.0% | -2.2% | | 1.4% | -0.1% | 1.5% | 50.4% | 1346 (115/43) |
| 1988−1996 | 29.6% | -0.1% | | -0.1% | 0.3% | -0.4% | 29.1% | 1360 (57/22) |
| TFP | | | | | | | | |
| 1969−1979 | 15.3% | -6.9% | | 1.6% | -0.8% | 2.4% | 10.8% | 1148(263/41) |
| 1979−1988 | 12.9% | -3.8% | | 0.4% | -0.8% | 1.2% | 10.2% | 1262 (91/42) |
| 1988−1996 | 5.7% | 0.6% | | 0.4% | 0.3% | 0.1% | 6.4% | 1304 (55/21) |

of TFP, the negative 'between' and 'cross' effects for TFP are more puzzling. Technically, the negative 'between' effect implies faster output growth at sites whose total factor productivity is below the industry average, and the negative 'cross' term indicates that positive growth of TFP is associated with negative output growth. The latter may be true if many firms in the dataset had spun off less efficient product lines or subsidiaries as part of their restructuring. While the 'between' effect is negative in almost all cases, the negative relationship between TFP growth and output growth is observed only during the bubble economy period.

Overall, we do not find any conclusive evidence for a misallocation among the group of continuing firms examined in this exercise. Compared to the 1977−1988 period, the between and cross effects are larger in most cases during the 1988−1996 period. Therefore, downsizing of relatively inefficient firms may have been more active during this latter period than the earlier period.

Next, we discuss changes in 'entry' and 'exit' effects over time. Note here that the positive sign on the 'exit' effect indicates a negative contribution to the overall growth rate, in accordance with equation 1.4 and equation 1.5. The 'net' entry effect is the difference between the 'entry' effect and the 'exit' effect. For the TFP decomposition, the estimated 'entry' and 'exit' effects are very similar across two types of decomposition for all periods.

When using labor productivity, the table shows 'net' entry reduces total productivity growth by about 0.3% or 0.4% during the sluggish period, while in prior periods, it boosted overall productivity growth by 1.5% to 3.1%. Both entry and exit contributions were weak during the sluggish growth period, but the 'entry' effect falls sharply during the sluggish growth period. Consequently, exit by relatively more profitable firms by itself accounts for much of the 'net' entry effect during the 1988−1996 period.

For TFP, the first result is that again, the 'net' entry effect is very small during the period of sluggish growth. However, the 'entry' effect did not change at all in the 1988−1996 period in comparison with the 1979−1988 period. Therefore, the reduction is entirely brought about by the drop in the contribution of the 'exit' effect. Here, we observe that the contribution of the 'exit' effect becomes suddenly negative (as the sign turns positive) during the sluggish growth period. The negative 'exit' effect implies that quite few firms with a TFP level higher than the industry average exited during this period. In both decompositions, the positive contribution made by entering firms during the sluggish period is still significant, constituting about 7% of total productivity growth, while the exit of relatively more productive firms during the same period leads to a reduction in productivity of approximately $5 - 6\%$ of total productivity growth.

Overall, these results indicate the following. The results for 'between' and 'cross' effects are somewhat puzzling and inconclusive. Certainly, these results may be driven by an increase in capital intensity or spinning off of inefficient subsidiaries, which partly account for the cross-period differences. However, we do not find any obvious evidence which suggests that the 1990s were a particularly bad period in terms of the reallocation of labor input and output among continuing firms. At the same time, there has been a change in the contribution of net entry during the sluggish growth period. In particular, much of the reduction in TFP growth was attributed to the drop in 'exit' effect, as the 'entry' effect remained strong. The implications of these results are discussed in the next section.

## 1.5 Conclusion

Job reallocation exercises performed using the Nikkei financial dataset showed that job reallocation dynamics among large Japanese firms are mainly driven by job creation, and this job reallocation pattern does not seem to have changed much during recent years of sluggish economic growth. Moreover, the smaller role played by job destruction is more prominent in the non-manufacturing sector. When the job reallocation rate is decomposed into an idiosyncratic component and a sectoral/aggregate component, the dominance of the idiosyncratic component over the sectoral/aggregate component in driving the overall variation of job reallocation declined in the 1987−1997 period in the manufacturing sector. As mentioned before, the larger influence of the sectoral/aggregate component during this period appears consistent with the findings on stock return volatility by Hamao, Mei and Xu (2003). At the same time, the correlation between the idiosyncratic and the sectoral/aggregate components turned suddenly and significantly negative in the 1987−1997 period in the manufacturing sector, suggesting that idiosyncratic effects started to counterbalance sectoral/aggregate effects during this period. This may be caused by protective measures used by the government in response to negative sectoral/aggregate disturbances, but identifying the sources of this change will require further investigation.

The productivity decomposition exercises reveal that among continuing firms, we do not find strong evidence of the cleansing effect of recessions, as the results for 'between' and 'cross' effects do not suggest that the reallocation was poor during the sluggish growth period. Neither is the evidence found in the behavior of entering firms, as they seem to have made a strong contribution to the overall TFP growth rate during the sluggish growth period. However, exits of relatively more productive firms underscore that the cleansing effect is not at work. In other words, the malfunction of the reallocation mechanism seems to manifest itself in the exiting behavior of firms. These results also relate to the findings of Peek and Rosengren (2003) that financially troubled and heavily indebted companies had less difficulty accessing credit from major Japanese banks, as those banks sought to manipulate their balance sheets rather than fund their financially healthier counterparts. This type of financial practice may have led to the survival of the least productive firms, at the expense of less heavily indebted and more productive firms. Moreover, the strong and positive contribution of entry implies that the 'credit crunch' may not have been so significant. This is consistent with the findings by Motonishi and Yoshikawa (1999).

Within the framework of a search model, a dramatic increase in job destruction leads to a long period of high unemployment and lengthy recovery from recession, as job creation takes time due to the existence of search costs.[15] The examination of job reallocation using the Nikkei financial dataset revealed that the sluggish growth in Japan during the 1990s was not accompanied by a dramatic rise in job destruction. This fact can also be confirmed by the unemployment rate, which followed a gradual and mild increase instead of a sudden rise during this period. At the same time, the exit behavior of firms suggests an insufficient resource reallocation from less to more productive firms. Accordingly, this may possibly have extended the length of the sluggish growth period.

In the next chapter, I examine the nature of the labor input adjustment mechanism in Japan during the 1990s from a different angle. More specifically, I investigate the aggregate labor input responses to demand shocks in the manufacturing sector and the Iron and Steel industry, sectors whose employment has declined in recent years.

[15] For example, see Mortensen and Pissarides (1994).

# Chapter 2

# Input and Output Responses to Demand Shocks using an Interrelated Factor Demand Model

## 2.1 Introduction

This chapter investigates the labor input and inventory responses to demand shocks in the Japanese manufacturing sector, as well as the Iron and Steel industry, the largest beneficiary of the Employment Adjustment Subsidy (EAS), using an interrelated factor demand model developed in Topel (1982). I use monthly industry-level time-series data between January 1978 and November 2004. In order to evaluate changes in the adjustment mechanism in recent years, the entire series was divided into two parts after identifying a natural breakpoint in the demand shock processes. Subsequently, the responses of employment, work hours and inventories to demand shocks are compared between the period preceding and following the natural break point, which was identified as May 1992. The main findings are the following. First, demand shocks appear to have increased in volatility after 1992 in both the manufacturing sector and the Iron and Steel industry. Second, for the manufacturing sector, the adjustment mechanism shifted from one using inventories intensively to reliance more on employment and work hours. Finally for the Iron and Steel industry, the employment and inventory adjustments do not exhibit any systematic changes, while the work hour adjustment has become much more prevalent in recent years.

Topel (1982) provides a theoretical framework which relates inventory costs and temporary layoffs, and also provides an empirical model for testing. The theory predicts that, other things being equal, lower inventory costs and therefore active inventory adjustments are associated with less frequent layoffs, recalls and work hour adjustments to meet short-run demand fluctuations. Similarly, higher hiring/layoff costs increase the cost of frequent layoffs, and encourage more active inventory adjustments. While Topel (1982) does not estimate inventory costs and hiring/layoff costs, the prediction of an inverse relationship between inventory adjustment and temporary layoffs, in turn, is supported by his empirical results comparing several US manufacturing sectors between 1958−75.[1]

Hashimoto (1993) applies Topel's empirical framework to compare the labor adjustment mechanism of the manufacturing sector in two countries, the US and Japan. He uses monthly time series data from January 1967 to December 1986 for Japan, and from January 1961 to December 1984 for the US, and finds that while employers in the US manufacturing sector adjust employment to accommodate short-run fluctuations in demand, Japanese employers rely less on employment adjustment and more on the adjustment of work hours. His estimates of interrelated factor demand show that the employment elasticity to unanticipated demand shocks is much stronger in the US than in Japan (0.146 as opposed to 0.065) and the elasticity of work hours with respect to anticipated demand shocks is much weaker in the US in comparison with Japan (0.024 as opposed to 0.141).

Furthermore, Hashimoto splits the series in order to evaluate the impact of the Employment Insurance Law, which was enacted in 1975. The objective of this law was to encourage firms to sustain employment during temporary unfavorable shocks via the Employment Adjustment Subsidy (EAS) in order to prevent a rise in unemployment. Since firms are subsidized when they adjust output through a reduction in work hours instead of employment, mainly through temporary business closures, the subsidy program was expected to reduce frequent layoffs and increase the intensity of adjustment in work hours. Consequently, Hashimoto finds that employment became less responsive, while work hours became more responsive to demand shocks after 1975. More specifically, he finds that the employment elasticity to unanticipated (anticipated) current demand shocks falls from 0.30 (0.28) to -0.27 (-0.27) while the elasticity of work hours to unanticipated (anticipated) current demand shocks rises from -0.28 (-0.17) to 0.41 (0.12).

As the Japanese economy has gone through a period of significant transformation during the 1990s, the changes in the estimates of the interrelated factor demand model further elucidate

[1]The industries used in his analysis are Chemicals, Petroleum, Tires and Tubes, Fabricated Metals, Rubber and Plastics, Electrical Machinery and Primary Metals.

the impact as well as the nature of this transformation. Accordingly, in this chapter, I first update Hashimoto's results on the labor adjustment mechanism in the Japanese manufacturing sector using monthly time-series data from January 1978 to November 2004. The series were split into two parts, before and after May 1992, based on the Quandt statistic which uses Chow's structural breakpoint tests and the least square breakpoint estimate.[2] The results show that both employment and work hours adjustment became more intense, while inventory adjustment became less so after 1992.

While the 1990s marked the period of the greatest take-up of the Employment Adjustment Subsidy, the increase in the intensity of employment adjustment in the 1990s by itself does not invalidate Hashimoto's conjecture that the EAS reduces employment adjustment and encourages adjustments through work hours. This is because the changes in the underlying pattern of demand shocks also most likely affected employers' strategy for adjusting labor inputs. Furthermore, technological improvements are likely to have reduced search/hiring costs in some industries, while remaining high in those with high subsidy coverage, thereby limiting the aggregate impact of the subsidy. Therefore, it is difficult to evaluate the impact of the subsidy by comparing the results across time, as we can not completely isolate those effects that are brought about by the changes in the economic environment.

However, a more realistic explanation as to why the impact of the EAS is not visible in the manufacturing sector is that the EAS has had a very high concentration in certain sectors within manufacturing, and the overall size of subsidized work hours in the manufacturing sector as a whole is quite small. This point is particularly emphasized by the fact that the Iron and Steel sector alone took, on average, about half of the total annual subsidy bill between 1990 and 2002. Furthermore, the estimated average annual fraction of workers who are unutilized for production through the subsidy program in the Iron and Steel sector is only about 2%, a small fraction of the whole. The next chapter provides a further explanation of the details of industry selection, the subsidy coverage across industries, as well as the method used to estimate the size of subsidized

[2] As described later, both tests generate similar results.

workers using the data on the subsidy bill.

The EAS's high concentration in the Iron and Steel industry makes this industry an ideal candidate for the investigation of the potential impact of the EAS on labor adjustment using an interrelated factor demand model.[3] Here, the time-series data was again split into two parts at May 1992, and the resulting estimates are compared across periods. As described in the next chapter, the EAS bill dramatically increased after 1992, and therefore some of the impact of the EAS may be observed from this comparison. However, the changes in the underlying pattern of shock processes and the corresponding shifts in the employers' labor adjustment strategies makes it hard to isolate the impact of the subsidy. Albeit imperfect, one strategy would be to use the results of the manufacturing sector as a benchmark case, and examine how the results in the Iron and Steel industry differ from the general trend observed by the benchmark. The results on employment elasticity to demand shocks show that, in most cases, employment responses are insignificant and weak in the Iron and Steel industry even post-1992. This result stands in sharp contrast to that of the manufacturing sector. On the other hand, the response of work hours to demand shocks in Iron and Steel has strengthened after 1992. While part of the differences may simply be caused by institutional differences other than the EAS, these results do not contradict with the prediction that the EAS reduces employment's responses and increases the response of work hours to shocks.

Another noteworthy result is that inventory responses to demand shocks are much larger in size and more significant in the Iron and Steel industry compared to the manufacturing sector as a whole. This result is indicative of higher labor adjustment costs or lower inventory costs in the Iron and Steel sector compared to the average industry within the manufacturing sector. Higher adjustment costs, in turn, increase the benefits of the Employment Adjustment Subsidy and increase the take-up rates of the subsidy. Furthermore, while inventory adjustments become weaker and insignificant within the manufacturing sector after 1992, they remained strong and

[3] Note that the exercise carried out here is not a direct test of the impact of the EAS, since we cannot disentangle the institutional differences and the impact of the EAS. In order to test the impact of the EAS, we also need a dataset for the pre-EAS period, as in Hashimoto (1993). This was not done in this paper due to limited data.

significant in the Iron and Steel sector. This result reveals that labor adjustment costs continued to be high relative to inventory adjustment costs within Iron and Steel.[4]

Finally, output responses to demand shocks in the Iron and Steel sector are also investigated. The standard procedure outlined in Topel (1982) uses a seasonally unadjusted monthly time-series on shipments to construct the demand shock series, by decomposing the shipments series into a predictable and an unpredictable component. In order to evaluate the output responses to demand shocks, I used a demand instrument series constructed using the average growth rate of shipments of downstream industries.[5] The results are mixed. When using shipments to measure output, the output growth responses to unpredicted demand shocks rise after 1992, while when value added was used to measure output, the output responses to demand shocks fall after 1992. However, coefficients are not significantly different from each other before and after 1992.

The demand instrument exhibits a substantial increase in volatility after 1992. Higher volatility, in turn, can explain the rise in the subsidy take-ups, as volatility increases the need for frequent input adjustments. The implications of higher shock volatility on subsidy take-up decisions in the context of the theoretical framework given in the next chapter will be discussed in the appendix.

As for the output responses to shocks, the theoretical framework in the next chapter shows that, *ceteris paribus*, a rise in the number of subsidized workers increases output volatility, as the subsidy allows firms to hoard workers at smaller costs and meet short-term fluctuations in demand more easily. Therefore, the reduced value added sensitivity to demand shocks during the period of higher subsidy coverage contradicts the theoretical prediction. It requires a better demand instrument, or theoretical modifications, or both, to fill the theoretical and empirical discrepancy. One possible theoretical explanation for the reduced sensitivity of output is that

[4] According to *Survey on Employment Trend* published by the Ministry of Labor, Health and Welfare, the share of flexible workers such as part-time or temporary workers is among the lowest for the Iron and Steel industry throughout the 1990s.

[5] Obviously, we cannot use shipments series to construct demand shocks when shipments are also used to measure output, as the unpredictable component of demand shocks will be perfectly correlated with the output measure.

the input responses are non-linear in the size of demand shocks and/or there is a limit on the degree of input adjustments including the use of the subsidy. In these cases, the average input responses to shocks could decline with the volatility of shock processes. While this explains the reduced output sensitivity to demand shocks in the presence of high volatility, whether or not such modifications are necessary has not yet been discovered as empirical results on output responses are still inconclusive. Reconciling this issue will remain a future research agenda.

## 2.2 Description of the Interrelated Factor Demand Model

Topel's interrelated factor demand model captures the interdependence of input decisions among the following three variables: employment, work hours and inventories. It also allows us to distinguish the responses to unpredicted current shocks, predicted current and predicted future shocks. More specifically, the following set of equations are used to investigate the interrelated factor demand decision rules:

$$L_t = \alpha_{10} + \alpha_{11}L_{t-1} + \alpha_{12}H_{t-1} + \alpha_{13}I_{t-1} + \sum_{\tau=0}^{T} \beta_{1\tau}\widehat{q}_{t+\tau} + \lambda_1 q_t^u + trend, \tag{2.1}$$

$$H_t = \alpha_{20} + \alpha_{21}L_{t-1} + \alpha_{22}H_{t-1} + \alpha_{23}I_{t-1} + \sum_{\tau=0}^{T} \beta_{2\tau}\widehat{q}_{t+\tau} + \lambda_2 q_t^u + trend, \tag{2.2}$$

$$I_t = \alpha_{30} + \alpha_{31}L_{t-1} + \alpha_{32}H_{t-1} + \alpha_{33}I_{t-1} + \sum_{\tau=0}^{T} \beta_{3\tau}\widehat{q}_{t+\tau} + \lambda_3 q_t^u + trend. \tag{2.3}$$

Here, $L_t$, $H_t$ and $I_t$ refer to employment, work hours and inventory in natural logarithms at time $t$, $T$ is the planning horizon, $\widehat{q}$ is the forecasted component of demand while $q_t^u$ captures the unpredicted component (i.e. $q_t - \widehat{q}_t$), and $\alpha$, $\beta$, and $\lambda$ are the impact elasticity coefficients to be estimated. As explained by Topel, forecasted as well as unforecasted components of shipments drive the model.

The following propositions are given by Topel: first, the speed of adjustment parameters, given by $\alpha_{jj}$, are expected to increase as the labor adjustment costs increase or inventory costs decrease. These parameter values equal zero when inputs are freely variable and unity when they are fixed. Second, a rise in current predicted shipments ($\widehat{q}_t$) or in current unpredicted shipments

($q_t^u$) increases both employment and work hours while reducing inventories. A lower cost of inventories as well as higher labor adjustment costs increase the inventory and work hour responses to current predicted or unpredicted shocks, whereas they reduce the employment responses to those shocks. Employment and work hour adjustments for predicted shocks could be larger than for unpredicted shocks, if adjustment takes time and needs to be pre-arranged. Third, a rise in future expected shipments ($\sum_{\tau=1}^{T} \widehat{q}_{t+\tau}$) should increase the demand for employment, work hours and inventories. These effects are smaller the longer the planning horizon, and the higher the inventory and labor adjustment costs.

Next, it is assumed that expected monthly demand values depend only on the past values of shipments and not on the other endogenous variables. More specifically, the demand condition, characterized by the monthly series on log shipments, $q_t$, follows a seasonally differenced autoregressive integrated moving average (ARIMA) process of the following form:

$$A_a(L)(1-L)(1-L^{12})q_t = (1-\delta L^{12})M_m(L)u_t \tag{2.4}$$

where $L$ represents a lag operator, $A_a(L)$ and $M_m(L)$ are polynomials of orders $a$ and $m$ respectively in the lag operator, $\delta$ is a seasonal moving average parameter, and $u_t$ is the white noise error term. The best fit model was chosen based on the Akaike information criterion, Schwartz information criterion and correlogram.

Following Topel (1982), an additional structure is imposed on the lead distributions of $\beta_{j\tau}$. Namely, it is assumed that they follow a third order Almon polynomial, thereby requiring the shortest planning horizon to be 4 months. The planning horizons for both the manufacturing sector and the Iron and Steel industry are set at 6, 9 and 12 months.

Finally, for the Iron and Steel industry only, the output responses to demand shocks are investigated. Here, the demand instrument $d_t$ was used instead of shipments to model the demand condition. As described in the next section, $d_t$ is the weighted average log growth rate of shipments of downstream industries and not the level.[6] The demand shock was assumed to follow a seasonally differenced autoregressive moving average (ARMA) model, instead of an ARIMA model. Now,

[6]The shipments figures are normalized by the year 2000 values so that I could not use the actual level.

by totally differentiating an equation similar to the previous ones with respect to time, we can estimate the output growth responses using the following equation:

$$
\begin{aligned}
dY_t &= \alpha_{40} + \alpha_{41} dL_{t-1} + \alpha_{42} dH_{t-1} + \alpha_{43} dI_{t-1} \\
&\quad + \alpha_{44} dY_{t-1} + \sum_{\tau=0}^{T} \beta_{4\tau} \widehat{d}_{t+\tau} + \gamma_4 d_t^u + trend.
\end{aligned}
\tag{2.5}
$$

Here, $Y_t$ refers to the log of real output, and $dY_t = Y_t - Y_{t-1}$. As mentioned previously, I use both real shipments and real value added as a measures of real output.

## 2.3 Description of the Data

Monthly seasonally unadjusted series on shipments, employment, work hours and inventories within the manufacturing sector as well as the Iron and Steel industry between January 1978 and November 2004 are used to obtain the estimates for the interrelated factor demand model. As discussed in Topel (1982), the use of seasonally unadjusted series is important since "the transitory and highly predictable character of seasonal fluctuations makes them prime candidates for inventory smoothing and temporary layoffs."[7]

The data on shipments and inventories are taken from the *Indices of Industrial Production* published by the Japanese Ministry of Economy, Trade and Industry.[8] Nominal values of the indices of shipments and inventories for each industry are deflated using monthly *Corporate Good Price Indices* (CGPI) constructed by the Bank of Japan. The data on employment and work hours are taken from *Monthly Labor Statistics* provided by the Japanese Ministry of Health, Labor and Welfare.[9] Note that the statistics on employment and work hours are based on establishments with

[7] Footnote 16 in Topel (1982).

[8] The series are normalized by the value for the year 2000. The historical monthly series on shipments, value added, inventories and inventory ratio by industries within the manufacturing sector are available for review and downloading on METI's website in both English and Japanese. The English site is found at: http://www.meti.go.jp/statistics/index.html

[9] Note that the statistics used here are based on the old industrial classification used prior to year 2004. Various compilations of labor related data including Monthly Labor Statistics are provided on line by the Japan Institute for Labor Policy and Training at http://stat.jil.go.jp/ in Japanese.

more than 30 employees. Unfortunately, monthly statistics that include smaller establishments are available only since 1990.[10]

To investigate the output responses to demand shocks in the Iron and Steel industry, a demand instrument is constructed using the information on the activity of downstream industries. Note that I was unable to use the actual level of shipments made by the downstream industries, since the industrial monthly figures are normalized by the year 2000 values in *Indices of Industrial Production*. Instead, the demand instrument is constructed as the average growth rate of shipments of downstream industries, weighted by the annual share of consumption of the Iron and Steel industry's shipments.

Following Bartelsman, Caballero and Lyons (1994), the weights used to calculate the demand instrument are taken from an annual input-output table, and here, by the 2-digit industry classifications given by *Indices of Industrial Production*. More specifically, letting $w_{ij}$ be the element on the $i$th row and $j$th column of the input-output table in a particular year, and $dq_{jt}$ the log growth rate of the index of monthly shipments of industry $j$ at time $t$, the monthly demand instrument for industry $i$ can be written as follows:

$$d_{it} = \sum_{j \neq i} \frac{w_{ij}}{\sum_{j \neq i} w_{ij}} dq_{jt}. \tag{2.6}$$

Note that the subscript $t$ refers to month. Although the weight $w_{ij}$ varies every year, I did not add a subscript so as to keep the presentation simple. Since this exercise is only performed for the Iron and Steel industry, the index $i$ refers to Iron and Steel and $j$ refers to other industries.

The annual input-output table is taken from the *Japan Industry Productivity Database* (JIP database).[11] Nominal values of shipments are again deflated using CGPI.[12] Since industry classifications differ between the JIP database and the *Indices of Industrial Production*, a matching

[10]The correlation between the two statistics, one based on establishments with more than 30 employees and the other based on establishments more than 5 employees, is very high for both employment and work hours in the manufacturing as well as the Iron and Steel sectors.

[11]The JIP database is made available both in Japanese and English by Kyoji Fukao on his website: http://www.ier.hit-u.ac.jp/~fukao/english/data/index.html.

[12]Note that since the CGPI does not have categories for 'furniture', 'leather products' and 'rubber products,' the indices for 'other manufacturing products' are used for each.

between the two classifications was required. Table ($C$.1) in the appendix shows the concordance of industry classifications. Note that the broad industry classification of the *Indices of Industrial Production,* which is equivalent to a two-digit level classification, was used for the correspondence, as deflators are available only at this level. Furthermore, while we can construct time-varying weight $w_{ij}$ for each year, the JIP database ends in 1998. Hence, the weights for 1998 are used for the remainder of the period until November 2004.

## 2.4 Results

### 2.4.1 Manufacturing Sector

First, I present results for the manufacturing sector in order to compare with Hashimoto's results. Figure (2.1) shows log shipments, employment, work hours and inventories from the manufacturing sector. The figure on shipments shows that the reduction in the trend growth rate occurred around 1992. Employment also starts to fall around 1992, and average work hours drop in 1988, reaching a new steady state level in 1992. This drop in hours was arguably caused by changes in the Labor Standards Law that gradually reduced statutory work hours from 48 hours to 40 hours a week. However, visual inspection of shipments and employment suggests a deeper regime change in the manufacturing sector, unrelated to the changes in the labor law, around 1992.

In order to model the time series process for demand, the best parsimonious specification which removed autocorrelation in the residuals was chosen based on the Akaike information criterion.[13] Once the model was chosen, I tested for a structural break between 1989 and 1992 using the Quandt statistic and the least squares break-date test, as the visual inspection suggested a break around this period.[14] More specifically, F-statistics from Chow structural break tests are plotted over possible structural breakpoint dates and the date with the largest value was picked

[13] I experimented with a number of specifications with both lags ranging from one to four. The selection criterion chosen are AR(4) and MA(4).

[14] As discussed in Hansen (2001), the least squares test is a better test for the structural break, and the Quandt statistic produces the same result as the least squares test only "in linear regression when the Chow test is constructed with 'homoskedastic' form of the covariance matrix."

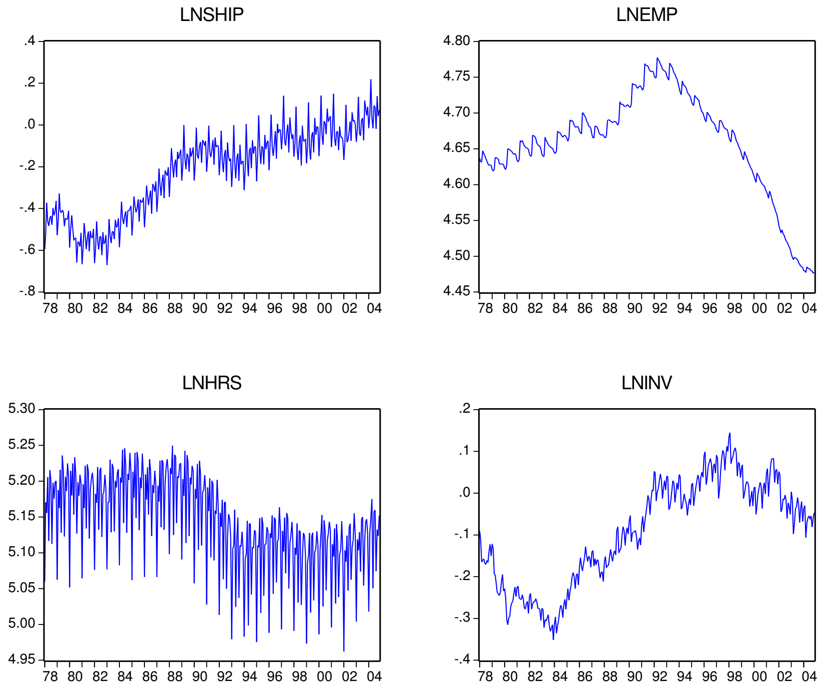


Figure 2.1: Monthly series on shipments, employment, work hours and inventories (in logs) in the manufacturing sector for January 1978−November 2004. Data source: the original series of shipment and inventory indices are taken from *Indices of Industrial Production* while the data on employment and work hours for establishments with more than 30 employees are taken from *Monthly Labor Statistics*.

as the Quandt statistic. Similarly, the sum of squared errors are calculated for possible structural breakpoint dates, and the date which minimized the residual variance was chosen as the least squares breakpoint date.

The results are similar in both cases. The Quandt statistic reaches its peak in April 1992 and May 1992, while the sum of squared errors was the smallest in March 1992 and May 1992. Here, I chose May 1992 as the month for a structural break.[15] In addition to the slowdown in the trend output growth occurring around that time, the standard deviation of log shipments, detrended by a Hodrik-Prescott filter, increased by 25% in comparison to the period preceding May 1992. The higher volatility in short-run fluctuations of output within the manufacturing sector suggests more turbulent demand conditions during the 1990s.

[15]As explained later, the same test for the Iron and Steel sector also exhibited similarly strong evidence for a break in May 1992.

Table 2.1: The estimates of the interrelated factor demand model in the manufacturing sector, 9-month forecast horizon.

| | Employment ( $L_t$) | | Hours ($H_t$) | | Inventories ($I_t$) | |
|---|---|---|---|---|---|---|
| | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 |
| Demand: | | | | | | |
| Current Unpredicted | 0.002 | 0.027** | 0.065 | 0.216*** | -0.202*** | 0.053 |
| | (0.012) | (0.012) | (0.060) | (0.059) | (0.063) | (0.061) |
| Current Predicted | 0.009 | 0.043*** | 0.048 | 0.313*** | -0.165*** | 0.118** |
| | (0.010) | (0.012) | (0.053) | (0.057) | (0.056) | (0.059) |
| Future Predicted | 0.001 | 0.030*** | 0.049* | 0.297*** | 0.053* | 0.009 |
| | (0.006) | (0.008) | (0.028) | (0.040) | (0.030) | (0.041) |
| Lagged Dep. Variables: | | | | | | |
| $L_{t-1}$ | 1.017*** | 0.969*** | -0.499*** | -0.491*** | 0.451*** | 0.037 |
| | (0.024) | (0.018) | (0.125) | (0.090) | (0.131) | (0.093) |
| $H_{t-1}$ | 0.025 | 0.001 | 0.113 | -0.067 | 0.115 | 0.048 |
| | (0.016) | (0.018) | (0.084) | (0.091) | (0.089) | (0.094) |
| $I_{t-1}$ | -0.012** | 0.002 | -0.090*** | 0.068*** | 0.916*** | 0.950*** |
| | (0.006) | (0.006) | (0.030) | (0.028) | (0.032) | (0.029) |
| Number of obs. | 149 | 127 | 149 | 127 | 149 | 127 |
| R-squared | 0.9971 | 0.9996 | 0.9645 | 0.9721 | 0.9844 | 0.9702 |
| Durbin-Watson statistics | 2.12 | 2.02 | 2.13 | 2.22 | 1.67 | 1.93 |
| F-statistics | 2182 | 12091 | 174 | 184 | 405 | 173 |

After splitting the sample in two, I estimated various ARIMA and again chose the best parsimonious model for each group.[16] Table (2.1) shows the estimates of the interrelated factor demand model with the planning horizon set equal to 9 months.[17] The standard errors are reported inside parenthesis. Note that the coefficients for future predicted demand are the sum of the coefficients for future months.

Prior to 1992, employment responses to demand shocks were positive but they were small in

[16] I used AR(2) and MA(3) for the first period and AR(1) and MA(3) for the second period. In both cases, the resulting disturbance terms are not autocorrelated.

[17] The original interrelated factor model proposes that we include a lagged value of other factors or stocks such as materials on the right hand side of each equation. I included 'raw material inventory-consumption ratio' on the right hand side as a robustness check, but the main results did not change. The coefficient on the raw material ratio is significant only for the work hours' regression, and the sign is negative as expected.

size, and insignificant. However, the coefficients for all shocks become bigger and significant after 1992. The same pattern is observed for work hours, with an even greater degree of significance. Finally, the table shows that inventory adjustment becomes less responsive to demand shocks after 1992. Moreover, the coefficients have expected signs before 1992, but they have wrong signs after 1992 for current unpredicted and predicted demand shocks. Finally, all shock response coefficients before and after 1992 are significantly different from each other at the 5% level for both employment and work hours. For inventories, only coefficients on current unpredicted shocks are significantly different.

Table (2.2) and (2.3), respectively, show similar tables with the planning horizon set equal to 6 and 12 months. The evidence for the change in employment responses to shocks after 1992 is not as strong as with a 9-month forecast horizon. For employment, the coefficients before and after 1992 are no longer significantly different from each other at the 5% level for current unpredicted and current predicted shocks. The change in the sensitivity of work hours is strong in both tables and hence robust across various planning horizons. Again, for work hours, the coefficients before and after 1992 are significantly different from each other for all shock measures. The pattern of changes in inventory responses was also preserved across different planning horizons.

Overall, these results imply that there has been a shift in the adjustment style, from heavy reliance on inventories as opposed to employment and work hours, to reliance more on employment and particularly work hours with less emphasis on inventories. One possible explanation is that before 1992, the trend growth rate in the manufacturing sector was higher and consequently, short-run fluctuations in demand carried less weight in employers' labor input decisions. In other words, employers ignored the short-run fluctuations in demand to make employment decisions, and used inventory adjustment almost exclusively to accommodate the fluctuations. This view is consistent with the practice of life-time employment, which Japanese firms favored during the period of post-war high economic growth. However, after the collapse of the bubble economy in the early 1990s, employers in the manufacturing sector started to pay more attention to demand in making employment decisions. Alternatively, lower labor adjustment costs, as reflected by an

Table 2.2: The estimates of the interrelated factor demand model in the manufacturing sector, 6-month forecast horizon.

| | Employment ( $L_t$) | | Hours ($H_t$) | | Inventories ($I_t$) | |
|---|---|---|---|---|---|---|
| | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 |
| Demand: | | | | | | |
| Current Unpredicted | -0.002 | 0.018 | 0.067 | 0.302*** | -0.205*** | 0.090 |
| | (0.013) | (0.013) | (0.067) | (0.064) | (0.072) | (0.069) |
| Current Predicted | 0.0003 | 0.027 | 0.041 | 0.514*** | -0.148** | 0.215** |
| | (0.013) | (0.019) | (0.067) | (0.093) | (0.072) | (0.099) |
| Future Predicted | 0.007 | 0.034*** | 0.043* | 0.315*** | 0.030 | 0.050 |
| | (0.005) | (0.008) | (0.024) | (0.036) | (0.026) | (0.039) |
| Lagged Dep. Variables: | | | | | | |
| $L_{t-1}$ | 1.040*** | 0.967*** | -0.531*** | -0.480*** | 0.372*** | 0.088 |
| | (0.022) | (0.018) | (0.113) | (0.088) | (0.121) | (0.094) |
| $H_{t-1}$ | 0.029* | -0.013 | 0.121 | -0.011 | 0.091 | 0.054 |
| | (0.017) | (0.018) | (0.084) | (0.086) | (0.090) | (0.092) |
| $I_{t-1}$ | -0.013** | 0.004 | -0.090*** | 0.052* | 0.922*** | 0.945*** |
| | (0.006) | (0.006) | (0.030) | (0.027) | (0.032) | (0.029) |
| Number of obs. | 152 | 130 | 152 | 130 | 152 | 130 |
| R-squared | 0.9972 | 0.9996 | 0.9641 | 0.9725 | 0.9852 | 0.9707 |
| Durbin-Watson stat. | 2.08 | 2.09 | 2.13 | 2.23 | 1.68 | 2.01 |
| F-stat. | 2361 | 12614 | 176 | 192 | 436 | 181 |

increase in the use of part-time workers, may have allowed employers to accommodate short-term fluctuations in demand more easily. Another interesting observation is that inventory began to play a lesser role in demand buffering and work hours took on a much larger role. In sum, the role of labor input adjustment started to outweigh that of inventories after 1992.

Compared to Hashimoto's results for the period 1967−1986, I observe smaller employment and work hours responses to current predicted and unpredicted shocks, but similar inventory responses. However, the coefficients for employment and work hours before 1992 are not significantly different from zero in most cases for both Hashimoto and myself. When Hashimoto splits the sample into two, 1967−1974 and 1975−1986, he observed negative and significant employment responses to demand shocks in the latter period. This was not observed in my results for the 1978−1992 period. Furthermore, Hashimoto found that the work hours' response to the current

Table 2.3: The estimates of the interrelated factor demand model in the manufacturing sector, 12-month forecast horizon.

| | Employment ( $L_t$) | | Hours ($H_t$) | | Inventories ($I_t$) | |
|---|---|---|---|---|---|---|
| | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 |
| Demand: | | | | | | |
| Current Unpredicted | 0.004 | 0.016 | 0.046 | 0.146*** | -0.175*** | 0.015 |
| | (0.012) | (0.011) | (0.062) | (0.054) | (0.065) | (0.054) |
| Current Predicted | 0.010 | 0.024*** | 0.027 | 0.207*** | -0.103* | 0.055 |
| | (0.010) | (0.008) | (0.050) | (0.041) | (0.052) | (0.041) |
| Future Predicted | -0.012 | 0.030*** | 0.070* | 0.310*** | 0.004 | 0.038 |
| | (0.007) | (0.009) | (0.038) | (0.045) | (0.040) | (0.044) |
| Lagged Dep. Variables: | | | | | | |
| $L_{t-1}$ | 0.985*** | 0.974*** | -0.420*** | -0.504*** | 0.272* | -0.001 |
| | (0.028) | (0.020) | (0.146) | (0.097) | (0.152) | (0.097) |
| $H_{t-1}$ | 0.033* | -0.006 | 0.098 | -0.115 | 0.142 | -0.002 |
| | (0.017) | (0.019) | (0.086) | (0.095) | (0.090) | (0.095) |
| $I_{t-1}$ | -0.006 | 0.003 | -0.097*** | 0.075*** | 0.932*** | 0.954*** |
| | (0.006) | (0.006) | (0.032) | (0.029) | (0.034) | (0.029) |
| Number of obs. | 146 | 124 | 146 | 124 | 146 | 124 |
| R-squared | 0.9967 | 0.9995 | 0.9641 | 0.9705 | 0.9831 | 0.9700 |
| Durbin-Watson stat. | 2.18 | 2.06 | 2.13 | 2.11 | 1.75 | 1.89 |
| F-stat. | 1886 | 10736 | 168 | 170 | 363 | 166 |

predicted shock is significant for the 1975−1986 period, while this was insignificant in my sample for the 1978−1992 period.

While Hashimoto's concludes that the reduction in employment responses in the manufacturing sector after 1975 may be caused by the Employment Adjustment Subsidy, my results somewhat undermine this conclusion, as employment responses were strengthened during the 1990s, when the subsidy bill was at its highest. As mentioned earlier, this is not to claim that the EAS does not affect employment responses to shocks. Rather, the results suggest that the impact of the EAS on the manufacturing sector as a whole is probably limited, due to small and highly concentrated coverage relative to the size of the entire sector.[18] Given that the Iron and Steel industry receives

[18]Part of the heterogeneity in subsidy receipts across industries may be related to the fact that the Japanese government actively selected the four-digit industries to which the subsidy was targeted between 1975 and 2000. However, the particularly high take-up rates in certain industries such as the Iron and Steel industry seems to

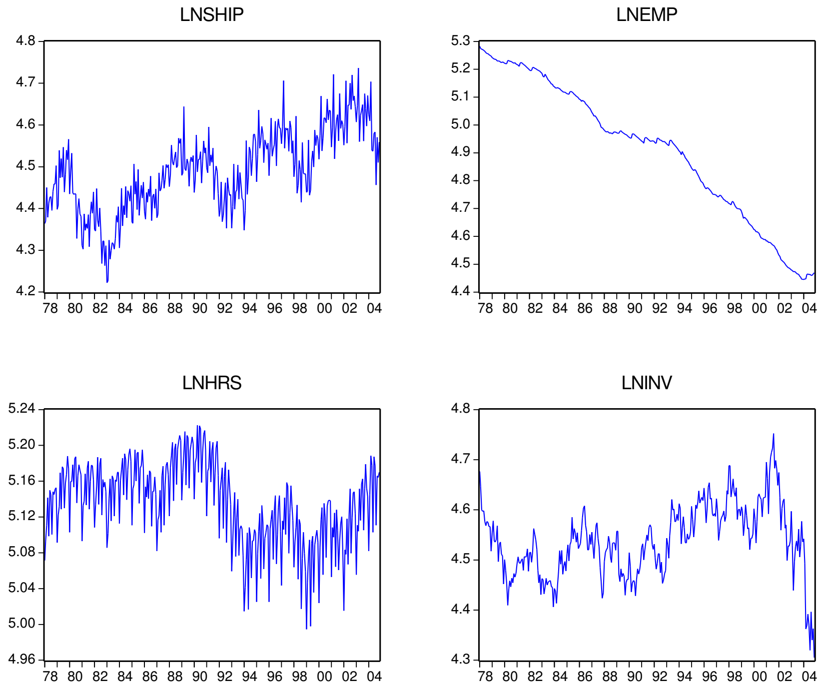


Figure 2.2: Monthly series on shipments, employment, work hours and inventories (in logs) in the Iron and Steel industry for January 1978−November 2004. Data source: the original series of shipment and inventory indices are taken from *Indices of Industrial Production* while the data on employment and work hours for establishments with more than 30 employees are taken from *Monthly Labor Statistics*.

about half of the total subsidy on average every year from 1990 to 2002 and the EAS bill started to take on a dramatically higher level after 1992, it seems worthwhile to investigate how input adjustment mechanism changed in this industry after 1992. While this is not a direct test of the impact of the EAS, the contrast between the manufacturing sector is likely to highlight some institutional factors as well as the potential impact of the EAS. This is the subject to which I turn next.

### 2.4.2 Iron and Steel Industry

Figure (2.2) shows log of shipments, employment, work hours and inventories in the Iron and Steel industry. The figure on shipments shows that unlike the manufacturing sector, there is no obvious change in the trend growth rate during this period. However, employment in this

underscore its high labor adjustment costs.

industry has been in decline during the entire period, reflecting an increase in capital intensity over the long-run. As in the manufacturing sector, work hours reach a lower steady-state level around 1992 in response to changes in the labor law.

I repeated my earlier procedures to estimate the form of the data generating process for shipments and to search for structural breaks.[19] Both the Quandt statistic and the least squares breakpoint tests indicated that the highest probability of a structural break was found in May 1992, and therefore the sample was split into two at this breakpoint.[20] Although the change is smaller than in manufacturing, the standard deviation of log shipments, detrended by a Hodrik-Prescott filter, increases by 11% after May 1992, thereby again indicating an increased turbulence in demand conditions during the 1990s. Subsequently, I estimate two separate data generating processes for the demand.[21]

Table (2.4) shows the estimates of the interrelated factor demand model for Iron and Steel, with the forecast horizon set equal to 9 months. Employment responses to current predicted and unpredicted shocks are not significant at 10% in either period. One of the coefficients on future predicted demand is significant, but both coefficients have the wrong sign. As for work hours, the size of adjustment increases in response to both current predicted and unpredicted shocks, and the increase in the size of the coefficients as well as the degree of significance is particularly dramatic for the current predicted shock. The inventory adjustment to current predicted and unpredicted shocks does not change much after 1992. The inventory coefficients all have the correct sign except for the future predicted shock before 1992. Overall, the table shows that the main change is observed in the adjustment of work hours.

Table (2.5) and (2.6) show the estimates of the same model, but with forecast horizons set equal to 6 months and 12 months respectively. The results are quite similar. In general, these tables do not offer conclusive evidence for any change in the employment response. While in all

[19]Here, The Akaike information criterion selects an AR(3) and MA(4).

[20]As mentioned previously, this break-date coincides with the time the EAS bill started to take on a dramatically higher level.

[21]For the first half, AR(1) and MA(2) are selected while for the second half, AR(3) and MA(2) are selected by the Akaike information criterion.

Table 2.4: The estimates of the interrelated factor demand model in the Iron and Steel industry, 9-month forecast horizon.

| | Employment ( $L_t$) | | Hours ($H_t$) | | Inventories ($I_t$) | |
|---|---|---|---|---|---|---|
| | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 |
| Demand: | | | | | | |
| Current Unpredicted | 0.010 | 0.019 | 0.109*** | 0.150** | -0.671*** | -0.562*** |
| | (0.013) | (0.013) | (0.040) | (0.058) | (0.073) | (0.068) |
| Current Predicted | 0.013 | 0.006 | 0.027 | 0.166*** | -0.431*** | -0.260*** |
| | (0.012) | (0.011) | (0.039) | (0.047) | (0.071) | (0.055) |
| Future Predicted | -0.012 | -0.022** | 0.059** | 0.051 | -0.032 | 0.050 |
| | (0.009) | (0.010) | (0.027) | (0.042) | (0.049) | (0.049) |
| Lagged Dep. Variables: | | | | | | |
| $L_{t-1}$ | 0.970*** | 0.945*** | 0.015 | -0.352** | 0.083 | 0.214 |
| | (0.021) | (0.035) | (0.068) | (0.152) | (0.124) | (0.178) |
| $H_{t-1}$ | 0.070*** | 0.026 | 0.664*** | 0.492*** | 0.045 | 0.108 |
| | (0.019) | (0.018) | (0.062) | (0.080) | (0.112) | (0.094) |
| $I_{t-1}$ | -0.0002 | 0.003 | -0.085*** | -0.049** | 0.919*** | 0.970*** |
| | (0.007) | (0.006) | (0.021) | (0.024) | (0.038) | (0.029) |
| Number of obs. | 150 | 125 | 150 | 125 | 150 | 125 |
| Akaike info. Criteria | -8.95 | -8.76 | -6.63 | -5.80 | -5.43 | -5.48 |
| Schwarts Criteria | -8.53 | -8.29 | -6.21 | -5.33 | -5.01 | -5.01 |
| R-squared | 0.9995 | 0.9996 | 0.9369 | 0.9120 | 0.8944 | 0.9367 |
| Durbin-Watson stat. | 2.06 | 1.89 | 2.35 | 2.28 | 1.50 | 1.59 |
| F-stat. | 12034 | 14756 | 96 | 54 | 55 | 77 |

cases the coefficient on current unpredicted shocks becomes somewhat stronger, there is no robust evidence for a change in the responsiveness of employment to current predicted shocks. As for the adjustment in work hours in response to current predicted and unpredicted shocks, the coefficients become stronger in terms of size and significance in all cases except for the unpredicted shock with the 12-month forecast horizon. Finally, in all specifications, only work hours' coefficients on current predicted shocks, before and after 1992, are significantly different from each other.

The evidence, overall, indicates that there are two main changes in the labor adjustment mechanism. First, the employment response to current unpredicted shocks became somewhat stronger after 1992. However, this result is not so conclusive because the coefficients are only significant in one case. Furthermore, the size and the significance of this increase in most cases

Table 2.5: The estimates of the interrelated factor demand model in the Iron and Steel industry, 6-month forecast horizon.

| | Employment ( $L_t$) | | Hours ($H_t$) | | Inventories ($I_t$) | |
|---|---|---|---|---|---|---|
| | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 |
| Demand: | | | | | | |
| Current Unpredicted | 0.006 | 0.032* | 0.110** | 0.249*** | -0.659*** | -0.688*** |
| | (0.014) | (0.016) | (0.045) | (0.073) | (0.084) | (0.091) |
| Current Predicted | 0.007 | 0.018 | 0.017 | 0.321*** | -0.367*** | -0.452*** |
| | (0.020) | (0.017) | (0.063) | (0.074) | (0.117) | (0.093) |
| Future Predicted | -0.005 | -0.024** | 0.059** | 0.069 | 0.033 | 0.066 |
| | (0.008) | (0.009) | (0.025) | (0.042) | (0.046) | (0.052) |
| Lagged Dep. Variables: | | | | | | |
| $L_{t-1}$ | 0.985*** | 0.959*** | 0.022 | -0.317** | 0.218* | 0.088 |
| | (0.020) | (0.034) | (0.065) | (0.152) | (0.120) | (0.190) |
| $H_{t-1}$ | 0.070*** | 0.044*** | 0.661*** | 0.532*** | 0.021 | 0.007 |
| | (0.019) | (0.017) | (0.061) | (0.074) | (0.114) | (0.093) |
| $I_{t-1}$ | -0.0005 | -0.001 | -0.080*** | -0.063*** | 0.914*** | 1.018*** |
| | (0.007) | (0.005) | (0.021) | (0.023) | (0.039) | (0.028) |
| Number of obs. | 153 | 128 | 153 | 128 | 153 | 128 |
| Akaike info. Criteria | -8.92 | -8.74 | -6.61 | -5.75 | -5.37 | -5.31 |
| Schwarts Criteria | -8.51 | -8.27 | -6.20 | -5.28 | -4.96 | -4.85 |
| R-squared | 0.9995 | 0.9996 | 0.9356 | 0.9115 | 0.8890 | 0.9454 |
| Durbin-Watson stat. | 2.03 | 1.88 | 2.33 | 2.35 | 1.44 | 1.43 |
| F-stat. | 12229 | 15241 | 96 | 55 | 53 | 93 |

are smaller than in the manufacturing sector. Secondly and more importantly, work hours became more responsive to shocks after 1992 although the magnitude of the change is not as dramatic as that in the manufacturing. This is particularly the case for current predicted shocks. Note that these results are not at odds with theoretical predictions of the impact of the EAS. The procedural lags in the application process should probably make the impact of the EAS more visible for predicted shocks than unpredicted shocks. Hence, it makes sense that the responsiveness of work hours to current predicted shocks has increased after 1992, while that for employment became weaker or remained insignificant after 1992.

Next, I present the results obtained using equation 2.5 for the estimation of the output responses to demand shocks. Figure (2.3) plots the demand instrument measure, $d_t$, between

Table 2.6: The estimates of the interrelated factor demand model in the Iron and Steel industry, 12-month forecast horizon.

| | Employment ( $L_t$) | | Hours ($H_t$) | | Inventories ($I_t$) | |
|---|---|---|---|---|---|---|
| | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 |
| Demand: | | | | | | |
| Current Unpredicted | 0.006 | 0.019 | 0.123*** | 0.109* | -0.638*** | -0.442*** |
| | (0.011) | (0.013) | (0.036) | (0.055) | (0.066) | (0.069) |
| Current Predicted | 0.007 | 0.002 | 0.058** | 0.163*** | -0.375*** | -0.130*** |
| | (0.008) | (0.009) | (0.026) | (0.039) | (0.048) | (0.049) |
| Future Predicted | -0.019* | -0.019* | 0.048 | 0.035 | 0.007 | 0.029 |
| | (0.010) | (0.010) | (0.030) | (0.042) | (0.056) | (0.053) |
| Lagged Dep. Variables: | | | | | | |
| $L_{t-1}$ | 0.960*** | 0.949*** | 0.006 | -0.404*** | 0.129 | 0.218 |
| | (0.023) | (0.035) | (0.073) | (0.149) | (0.133) | (0.187) |
| $H_{t-1}$ | 0.065*** | 0.038* | 0.651*** | 0.353*** | 0.079 | 0.128 |
| | (0.020) | (0.021) | (0.063) | (0.090) | (0.115) | (0.113) |
| $I_{t-1}$ | 0.0002 | 0.003 | -0.081*** | -0.028 | 0.926*** | 0.955*** |
| | (0.007) | (0.006) | (0.021) | (0.025) | (0.039) | (0.031) |
| Number of obs. | 147 | 122 | 147 | 122 | 147 | 122 |
| Akaike info. Criteria | -8.94 | -8.75 | -6.63 | -5.85 | -5.43 | -5.40 |
| Schwarts Criteria | -8.51 | -8.27 | -6.21 | -5.36 | -5.00 | -4.92 |
| R-squared | 0.9995 | 0.9996 | 0.9373 | 0.9166 | 0.8931 | 0.9301 |
| Durbin-Watson stat. | 2.08 | 1.88 | 2.34 | 2.14 | 1.53 | 1.64 |
| F-stat. | 11502 | 13660 | 94 | 56 | 53 | 67 |

January 1978 and November 2004. The structural break tests again suggest the highest probability of a structural break in May 1992, and the standard deviation of $d_t$ is 45% higher after 1992.[22] Table (2.7) shows the estimates of equation 2.5 with the planning horizon set equal to 9 months. Here, the indices of shipments and value added are used as measures of output. The correlation between $d_t$ and the growth rate of shipments (value added) is 0.84 (0.60).[23] Note that while the expected signs of the responses to current predicted and unpredicted shocks are positive for both measures of output, this may not be so for future predicted shocks: whereas a positive sign is

[22]As a comparison, the standard deviation of the growth rate of shipments (value added) is 25% (11%) higher after 1992.

[23]Furthermore, when shipments (value added) are regressed on current and lagged demand, the corresponding R-squared is 0.71 (0.40).

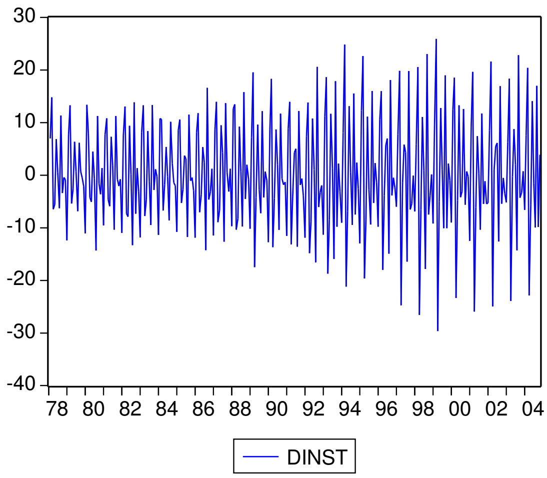


Figure 2.3: Monthly series on the demand instrument in the Iron and Steel industry for January 1978−November 2004. Data source: JIP database, *Indices of Industrial Production* and CGPI. See the text for the construction method used.

expected for value added, current shipments do not need to respond positively to future predicted shocks.[24]

When shipments are used as a measure of output, the coefficient on current unpredicted demand shocks becomes higher and more significant after 1992, while the opposite holds when value added is used. For current and future predicted shocks, the coefficients are mostly insignificant, and some have incorrect signs. This may be because the instrument does a poor job in capturing the predictable component of demand. Table (2.8) and (2.9) show the estimates of the same equation using 6-month and 12-month forecast horizons respectively. The key results on the output responses to demand shocks are essentially the same.

The difference in the observed direction of change in the responsiveness of shipments and value added is rather puzzling, but in all cases, the shock response coefficients before and after 1992 are not significantly different from each other. Theory suggests that holding other things equal, the subsidy program should lead to an increase in output volatility. This happens as the subsidy encourages firms to reduce production during downturns by subsidizing labor hoarding, while making output respond faster during upturns as firms avoid paying hiring costs. The

[24]While it is ideal to construct the measure of gross output as 'shipments plus change in inventories,' it was not done in this exercise due to the use of indices.

Table 2.7: The estimates of the output elasticity with respect to demand shocks in the Iron and Steel industry, 9-month forecast horizon.

| | Shipment ($Y_t$) | | Value Added ($Y_t$) | |
|---|---|---|---|---|
| | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 |
| Demand: | | | | |
| Current Unpredicted | 0.400*** | 0.565*** | 0.424*** | 0.345*** |
| | (0.085) | (0.097) | (0.072) | (0.071) |
| Current Predicted | -0.003 | 0.257 | 0.257** | -0.078 |
| | (0.154) | (0.189) | (0.130) | (0.142) |
| Future Predicted | -0.999* | -0.187 | -0.545 | -0.100 |
| | (0.519) | (0.473) | (0.425) | (0.360) |
| Lagged Variables: | | | | |
| $L_{t-1}$ | -0.306 | -0.057 | -0.301 | -0.662 |
| | (0.614) | (0.682) | (0.486) | (0.505) |
| $H_{t-1}$ | -0.181 | -0.093 | 0.149 | -0.071 |
| | (0.193) | (0.130) | (0.152) | (0.114) |
| $I_{t-1}$ | 0.599*** | 0.669*** | -0.089 | -0.085 |
| | (0.087) | (5.162) | (0.064) | (0.077) |
| $Q_{t-1}$ | -0.288*** | -0.130 | -0.046 | -0.256*** |
| | (0.069) | (0.095) | (0.089) | (0.095) |
| Number of obs. | 150 | 128 | 150 | 128 |
| R-squared | 0.9181 | 0.9350 | 0.8577 | 0.880 |
| Durbin-Watson statistics | 2.16 | 2.07 | 2.00 | 1.86 |
| F-statistics | 68.31 | 72.55 | 36.72 | 36.94 |

empirical counterpart to this prediction is the responsiveness of value added to demand shocks. However, we do not find any evidence that value added responses to shocks increased after 1992. The theoretical explanation for the reduced sensitivity may be that input responses are nonlinear in the size of the demand shock, or that there are upper limits on labor input adjustments as well as the use of the subsidy. Yet, since the coefficients are not significantly different from each other, whether or not an alternative framework is required is unclear. Filling in these empirical and theoretical discrepancies remains an item for future investigation.

Finally, the theoretical framework in the next chapter implies that higher volatility in shock processes increases the subsidy take-ups by increasing labor adjustment costs and therefore the benefit of the subsidy program. The result of a numerical experiment is given in the appendix. The intuitive reason for this is that the subsidy covers part of the costs for sustaining employment

Table 2.8: The estimates of the output elasticity with respect to demand shocks in the Iron and Steel industry, 6-month forecast horizon.

| | Shipment ($Y_t$) | | Value Added ($Y_t$) | |
|---|---|---|---|---|
| | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 |
| Demand: | | | | |
| Current Unpredicted | 0.413*** | 0.567*** | 0.431*** | 0.301*** |
| | (0.086) | (0.096) | (0.073) | (0.072) |
| Current Predicted | 0.010 | 0.299 | 0.195 | 0.043 |
| | (0.153) | (0.182) | (0.131) | (0.140) |
| Future Predicted | -1.059** | 0.002 | -0.586 | -0.059 |
| | (0.442) | (0.422) | (0.373) | (0.331) |
| Lagged Variables: | | | | |
| $L_{t-1}$ | -0.197 | -0.311 | -0.300 | -1.385*** |
| | (0.584) | (0.635) | (0.462) | (0.476) |
| $H_{t-1}$ | -0.155 | -0.021 | 0.057 | 0.014 |
| | (0.187) | (0.145) | (0.148) | (0.109) |
| $I_{t-1}$ | 0.594 | 0.641*** | -0.073 | -0.040 |
| | (0.087) | (0.116) | (0.064) | (0.075) |
| $Q_{t-1}$ | -0.287*** | -0.148 | -0.054 | -0.142 |
| | (0.069) | (0.088) | (0.089) | (0.093) |
| Number of obs. | 153 | 131 | 153 | 131 |
| R-squared | 0.9175 | 0.9377 | 0.8578 | 0.878 |
| Durbin-Watson statistics | 2.17 | 2.11 | 2.03 | 1.97 |
| F-statistics | 69.41 | 78.16 | 37.62 | 37.42 |

while firms reduce output through reduction in work hours, so that firms can avoid incurring firing/hiring costs to accommodate demand fluctuations. This theoretical prediction matches comfortably with the evidence that the EAS bill started to take on a dramatically higher level after the structural breakpoint date of 1992

## 2.5 Conclusion

In this chapter, I evaluate labor input and inventory responses to demand shocks in the manufacturing sector and in the Iron and Steel industry using an interrelated factor demand model. I also investigate the output response to demand shocks in the Iron and Steel industry. For this, a demand instrument was constructed using the growth rates of shipments of downstream industries. In all cases, we observe a structural break in the data generating process for demand

Table 2.9: The estimates of the output elasticity with respect to demand shocks in the Iron and Steel industry, 12-month forecast horizon.

| | Shipment ($Y_t$) | | Value Added ($Y_t$) | |
|---|---|---|---|---|
| | Pre-1992 | Post-1992 | Pre-1992 | Post-1992 |
| Demand: | | | | |
| Current Unpredicted | 0.395*** | 0.548*** | 0.420*** | 0.324*** |
| | (0.092) | (0.095) | (0.079) | (0.072) |
| Current Predicted | -0.023 | 0.187 | 0.234 | -0.058 |
| | (0.170) | (0.188) | (0.144) | (0.146) |
| Future Predicted | -0.675 | -0.153 | -0.464 | -0.124 |
| | (0.567) | (0.507) | (0.472) | (0.400) |
| Lagged Variables: | | | | |
| $L_{t-1}$ | -0.523 | -0.021 | -0.363 | -0.527 |
| | (0.623) | (0.691) | (0.503) | (0.525) |
| $H_{t-1}$ | -0.197 | -0.09 | 0.135 | -0.082 |
| | (0.201) | (0.155) | (0.162) | (0.117) |
| $I_{t-1}$ | 0.607*** | 0.608*** | -0.085 | -0.104 |
| | (0.088) | (0.132) | (0.065) | (0.080) |
| $Q_{t-1}$ | -0.290*** | -0.180* | -0.052 | -0.237** |
| | (0.070) | (0.095) | (0.091) | (0.097) |
| Number of obs. | 147 | 125 | 147 | 125 |
| R-squared | 0.9191 | 0.9386 | 0.8548 | 0.880 |
| Durbin-Watson statistics | 2.20 | 1.99 | 2.00 | 1.90 |
| F-statistics | 67.62 | 75.00 | 35.03 | 35.94 |

around May 1992. The volatility of demand increased substantially after the date of the structural break.

In the manufacturing sector, the results indicate that the burden of adjustment shifted from an inventory to the labor input. This could be because this period witnessed a decline in the trend growth rate. During the period of high trend growth, short-run fluctuations in demand arguably played a smaller role in influencing labor input decisions, while a slower growth rate during the 1990s made short-run fluctuations relatively more important in labor input adjustment decisions. A reduction in labor adjustment costs could also be another factor which led to the change in the style of labor adjustment. I also discussed that the impact of the Employment Adjustment Subsidy is unlikely to be visible in the manufacturing sector as a whole, due to the program's small size and its concentration in a few industries.

In the Iron and Steel industry, the primary recipient of the EAS, the results showed weak evidence for a change in the employment response to demand shocks. This deviation from the results for the manufacturing sector matches with the theoretical predictions of reduced employment volatility via the EAS, as the program encourages firms to sustain employment by allowing firms to 'ride out' unfavorable shocks through subsidization. Accordingly, the results indicate an increased response of work hours to shocks, particularly to current predicted shocks. The inventory responses in this sector showed a small difference across periods, and there is no regularity in the direction of the change across different planning horizons. However, the magnitude of the inventory responses in the Iron and Steel industry in general are much larger than in manufacturing as a whole. This highlights the fact that the Iron and Steel industry faces much higher labor adjustment costs and/or lower inventory costs than the average industry in the manufacturing sector. As the theory suggests, high labor adjustment costs could be the main reason for the high take-up rate of the subsidy within the Iron and Steel industry.

Finally, the results on the output responses to demand shocks in the Iron and Steel sector are mixed. Whereas shipment responses to current unpredicted shocks increased, value added responses to demand shocks fell after 1992. Yet, we find that coefficients are not significantly different from each other in all cases. I also discussed that the reduction in the response of value added does not match with the theoretical prediction, and we may have to make some modifications in order to theoretically describe these results. However, whether or not such modifications are necessary is yet to be discovered. Although unresolved issues still remain, the theory presented in the next chapter can comfortably explain why subsidy take-ups rose after 1992 as a result of increased volatility in the shock processes.

On the whole, the exercises in this section elucidate evidence of a structural change around 1992, and the corresponding reactions to this change in the manufacturing sector and the Iron and Steel industry. The manufacturing sector as a whole seems to have embarked on a shift in adjustment strategy to meet the more volatile shock processes, while the Iron and Steel sector, which relies heavily on the subsidy, did less to change its employment adjustment style. The theoretical implications of the EAS on long-run productivity, employment, output, as well as employment and output fluctuations over the business cycle are discussed in the next chapter.

# Chapter 3

# Labor Adjustment, Productivity and Output Volatility: An Evaluation of Japan's Employment Adjustment Subsidy

## 3.1 Introduction

This chapter examines the Employment Adjustment Subsidy (EAS), a core Japanese employment insurance policy since 1975.[1] The EAS program allows firms to reduce output during unfavorable business conditions without laying off workers by providing part of the costs of sustaining excess workers. The EAS policy has not yet been formally analyzed despite recent macroeconomic literature emphasizing job reallocation as a driving force behind business cycles. Therefore, the primary objective of this chapter is to point out some of the key implications of the policy through the application of a theoretical framework of heterogeneous establishments with aggregate uncertainty. In particular, this chapter investigates the impact of the EAS on average labor productivity, job flows and entry/exit rates at the steady-state. In addition, it examines the implications of the policy for the volatility of employment, output and productivity over business cycles.

Between 1990 and 2002, over 360 billion yen (over 3.6 billion US dollars) was spent on the EAS. On average between January 1991 and October 2001, about 170,000 establishments were eligible for the subsidy program.[2] According to the *1996 Establishment Census*, there are about 6.5 million establishments in Japan (excluding public service) with 770,000 in manufacturing.

[1]Since 1975, the employment insurance programs had three central interrelated projects: (1) *an employment stabilization project* that was carried out through the Employment Adjustment Subsidy, (2) *a skill development project* providing assistance to the management and development of job training centers, and (3) *a workers' welfare project* providing employment consultation. The employment stabilization project has been the most predominant of the three.

[2]Although, as described later, additional criteria set by the government in terms of past employment and output trends must be satisfied in order to receive the subsidy.

Consequently, the average number of targeted establishments corresponds to 2.6% of the total number of establishments, or approximately 20% of manufacturing establishments. The number of targeted establishments peaked at 411,000 in February 2000.

The EAS recipients are heavily concentrated in the manufacturing sector, with the largest beneficiary being the Iron and Steel industry. Between 1990 and 2002, over 93% of subsidy recipients were in manufacturing, and approximately 40% of the total bill during that period went to the Iron and Steel industry.[3] Although the program in principle involves the entire economy, to illustrate the theoretical implications of the program this chapter focuses on the Iron and Steel industry. The calibrated industry model developed later in this chapter will attempt to match moments of key variables obtained from the data for this industry.

With respect to the empirical background, Davis and Haltiwanger (1990, 1992, 1999) and Davis, Haltiwanger and Schuh (1996), using longitudinal data sets in the US manufacturing sector, expose the importance of idiosyncratic differences across establishments in explaining business cycle dynamics. Many theoretical frameworks analyzing industry dynamics, such as Jovanovic (1982), Hopenhayn (1992), Hopenhayn and Rogerson (1993), Ericson and Pakes (1995) and Campbell and Fisher (2000), also stress the importance of heterogeneity across firms when characterizing firm's production and entry/exit decisions. To the extent that the EAS interacts with such heterogeneity across establishments within an industry, the appropriate theoretical framework to analyze the effect of the policy must also encompass similar features.

In addition, prior research concerning the implications of differing labor market institutions,

[3]In October 2001, the Japanese government abolished industry selection completely in response to criticism that the program was skewed toward particular industries. Accordingly, the current guidelines provide that any establishment can receive the subsidy if specific and much stricter criteria are satisfied. Namely, the monthly average of the last *six* months' production has to drop by more than 10% and employment has to be less than or equal to, in comparison with the same months of the previous year. Previously, the monthly average of the last *three* months' production had to be strictly less, while employment had to be equal or less than the previous year. Furthermore, the subsidy cannot be given to establishments whose unfavorable business conditions are predicted to last for more than two years, and establishments are no longer able to receive the subsidy continuously for more than a year. Instead, they are required to take a year long hiatus, except during severe economic circumstances.

particularly European employment policies, has shown that labor market policies have an important effect on equilibrium job flows, unemployment and productivity. Hopenhayn and Rogerson (1993), for instance, illustrate that high firing costs in Europe, which interfere with the process of job reallocation, lead to a sizable reduction in employment and a drop in average productivity. Others have stressed the interactions between a changing economic environment and labor market policy. Ljungqvist and Sargent (1998) explain that generous unemployment benefits increase unemployment rates when the skill mix demanded in the labor market is rapidly changing. Other studies have linked multiple labor market policies. Bentola and Rogerson (1993), for example, demonstrate that wage compression in Europe tends to generate more volatile employment flows, fostering a policy that restricts the firing of workers. They argue that these institutional differences can account for the similarities in job flows and differences in unemployment between Europe and the US. Although this paper will not examine the political economy of the origin of the EAS, one of the chief objectives of the EAS has been to reduce the volatility of employment.

As wage compression can be considered as a precondition for firing restrictions, some labor market institutions, namely labor adjustment costs and wage rigidities, are likely preconditions for the EAS, since the subsidy will not be used if labor adjustment is costless or if wages can absorb shocks. Although there are few quantitative studies that estimate the cost of firing workers in Japan, there is some legal evidence that suggests that firing workers in Japan is generally very difficult, more similar to the European than the US case.[4] Moreover, the post-war tradition of life-time employment has encouraged firms to invest in building firm specific human capital.[5] This evidence indicates that adjusting employment has been quite costly in Japan. Accordingly, the EAS was designed in order to "assist firms in their efforts to maintain employment in times of temporary unfavorable business conditions owing to economic recession or changes in the industrial structure of the Japanese economy, as well as to promote employment stability and prevent

[4] Takashi Araki (2000) discusses the legal evidence of stringent firing restrictions in Japan from the perspective of corporate governance.

[5] A detailed discussion of the relationship between intensive human capital investment and the low turnover rate in Japan is provided by Mincer and Higuchi (1988).

unemployment."[6]

While there has not been a formal empirical study on the effect of the subsidy program, primarily due to the unavailability of data, some have attempted to examine if the EAS distorts employment behavior. For instance, Hashimoto (1993) uses monthly aggregate manufacturing data and concludes that employment became less sensitive, while working hours became more sensitive, to demand shocks after the subsidy program was enacted in 1975.[7] However, the results in the previous chapter demonstrated that the impact of the subsidy is hard to detect in the manufacturing sector during the 1990s in which subsidy take-up peaked. On the other hand, the results from the Iron and Steel industry indicated that the subsidy kept employment relatively unresponsive to demand shocks even during the period of higher volatility in the shock processes, while increasing the intensity of the adjustment through work hours.[8]

Another related yet unexplored empirical issue is that the presence of subsidized workers reduces measured productivity, since hoarded workers are not properly taken into account in employment statistics. This paper will attempt to estimate the number of unutilized workers through the subsidy program in the Iron and Steel industry, as well as the reduction in productivity that can be accounted for by the inclusion of subsidized workers in employment statistics. Then these estimates will be used for the calibration of the model. The model developed here offers insights beyond the direct effect of labor hoarding on productivity. The indirect effects of the EAS on the cyclical dynamics of output and employment generate a wide set of empirical predictions, testable in future research as more data becomes available.

The model exploits the theoretical framework of Hopenhayn (1992) and Hopenhayn and

[6] Japanese Ministry of Health, Labor and Welfare. "Guidebook for Employment Adjustment Subsidy," 2002.

[7] He also points out that the treatment of temporarily laid off workers in Japanese statistics as 'employed' explains part of the differences in unemployment rates between Japan and the US.

[8] On the contrary, the unemployment insurance (UI) system in the US encourages temporary layoffs instead of temporary business closures. Feldstein (1976, 1978) and Anderson and Meyer (1993) discuss the incentive for firms to increase temporary layoffs when the experience rating of firms' unemployment insurance is imperfect. Feldstein (1976) explains why employment instead of hours is reduced in response to negative demand shocks under the UI system in the US.

Rogerson (1993). The main advantage is that, as previously mentioned, this model allows for a heterogeneity across establishments and therefore allows us to evaluate the impact of the subsidy program on industry dynamics by explicitly modeling the equilibrium response of heterogeneous establishments. Unlike Hopenhayn and Rogerson, however, the consideration of labor supply decisions and thus the households' problem will be omitted to focus on the impact of the subsidy on establishment-level dynamics. Hence the analysis will be a partial equilibrium estimate of the change in overall industry dynamics caused by the subsidy program. Moreover, two-state aggregate uncertainty is added to the model, a feature that was not present in Hopenhayn and Rogerson (1993). Since the wage remains constant in the model, the aggregate uncertainty should be best interpreted as reflecting the partial equilibrium real impact of shocks net of their impact on wages.

In interpreting the impact of the subsidy on average labor productivity, a word of caution is in order: while firms are heterogeneous in the model, workers are homogeneous in the sense that productivity does not increase with tenure. The subsidy could increase average productivity if this feature were added to the model. This was not done in this paper because of the high concentration of the subsidy in sectors where the value of workers' skills seems to be depreciating faster in comparison to other sectors.[9] In my model, the difference between old and new workers is solely reflected in the hiring cost, which reduces output during the first period; the productivity of new and old workers is equalized afterwards.

I show that the subsidy program reduces steady-state average productivity primarily by increasing the number of unutilized workers (labor hoarding effect). Roughly speaking, the reduction in average productivity is more or less proportional to the fraction of subsidized workers: when the fraction of subsidized workers is about 1%, average productivity also falls by about 1%. At the same time, average firm-level employment increases and the job turnover rate falls with the subsidy. When the cost of the subsidy and the gains of reduced adjustment costs are included in

[9]For example, the subsidy seemed to have concentrated in those sectors with comparative disadvantage in the international market. The government often cites as reason for industry selection into the EAS as "unfavorable business conditions arising from the competition with cheaper imports from China" etc.

the calculation of average productivity, productivity is further reduced for reasonably sized labor adjustment costs, as the cost of the subsidy exceeds the savings on labor adjustment costs.[10]

The estimated direct impact of the subsidy on productivity is small, as the (estimated) average fraction of subsidized workers in the Iron and Steel sector between 1990 and 2002 is about 2.1%. However, the second moment features generated by my simulation exercises reveal that with realistic parameters, the subsidy program has a disproportionately large impact on output and employment dynamics over the business cycle. In particular, output volatility can increase by 3.5% even when the steady-state fraction of subsidized workers is around 1.6%. The intuitive reason for this result is that the subsidy increases the sensitivity of output to aggregate shocks symmetrically: following unfavorable shocks, the subsidy allows firms to reduce production without laying off workers, while following favorable shocks, firms are able to increase output without hiring new workers.

On the other hand, the subsidy reduces employment volatility. In some cases, the drop in employment volatility can be substantial, even when the fraction of subsidized workers is small. Below, I show that hiring and firing costs set equal to the annual wage of workers can reduce the volatility of employment by about 12% even if the fraction of subsidized workers is less than 2%. The reduction in employment volatility is achieved by the reduced sensitivity of job creation and destruction to aggregate shocks over the business cycle. The EAS also increases the average size of the firm while reducing average firm level output at the steady-state. Finally, the steady-state exit/entry rate as well as the steady-state job creation/destruction rate drop with the subsidy.

This chapter proceeds as follows: section (3.2) provides a brief background of the EAS as well as an overview of the employment and output trends obtained from the aggregate Iron and Steel industry data. I then calculate the direct impact of the EAS on TFP induced by labor hoarding, which later will be used for the calibration of the model. Section (3.3) lays out the theoretical framework of the industry model and provides analytical results. Section (3.4) shows results from solving a stochastic version of the model through numerical dynamic programming. I

[10]However, with high enough labor adjustment costs, it is possible that the savings on adjustment costs could exceed the cost of the subsidy.

present key statistical features from the stationary distribution of the model, as well as simulation exercises that compare the subsidy case with the benchmark case that sets the subsidy to zero. Section (3.5) offers my conclusions.

## 3.2 Background

### 3.2.1 Summary of the EAS

The Employment Adjustment Subsidy program was initiated in 1975 as a preemptive measure against unemployment. More specifically, it was initiated in response to policymakers' concern that the unemployment rate would rise following the first oil shock and the resulting changes in the industrial structure of the Japanese economy.[11] In principle, the subsidy was intended to help sustain employment during temporary unfavorable business conditions without incurring the loss associated with labor adjustment costs. This was mainly achieved by reimbursing a fraction of wages for establishments closing part or all of its operations, or a fraction of the cost of sending workers to other (unrelated) establishments. The subsidy was expected to lower unemployment as well as the cost of unemployment insurance by reducing the unemployment rate.

Prior to 2001, the government selected eligible industries, either entire four-digit sectors or subsectors, based on recent trends in industrial output and employment, or changes in the industrial structure, such as rising competition from foreign imports. The official selection criteria in terms of output and employment were: i) the average of the past three months' industrial production dropped more than 5% compared to the same months of the previous year, and ii) the average of the past three months' employment had not increased compared to the same months of the previous year.[12] Furthermore, additional special selection criteria were set in 1995 for more

[11] The Japanese Ministry of Labor reports that the EAS was originally designed in response to a recommendation by the OECD that the Japanese government prepare for higher unemployment arising from the transition from a growing to a mature economy. [Japanese Ministry of Labor, Employment Security Bureau (1999), p.14.] Another justification often provided was to assist firms, which had been the primary provider of job security often in the form of life-time employment, to sustain employment during difficult times.

[12] As for the employment criteria, it became 'a drop of 5% or more' between March 2000 and October 2001.

generous subsidy coverage: "as a result of an appreciation of the yen or economic globalization, the monthly average of the past six months' industrial production and employment fell or is predicted to fall more than 10% compared to the same season in one of the three previous years." The selection was not completely deterministic as explained by the government: the "selection is not solely based on figures but also determined in accordance with our objective of the prevention of unemployment."[13] The Japanese government abolished industry selection criteria in October 2001, replacing them with tougher establishment-level eligibility criteria.

Under the standard selection rules, industries were selected for one year with the possibility of an extension for an extra year if needed. Once selected, industries could be re-selected after a six-month break. For the special selection rules between 1995 and 2001, the selection period was set to two years with the possibility of an extension. Between 1990 and 2001, the unweighted average length of eligibility for a selected industry was 2.6 years with a maximum of 7 years. During the same period, about 96% of the selected four-digit industries or subcategories belonged to the manufacturing sector, of which about 14% belonged to Ceramic and Clay Products, 13% to General Machinery, 10% to Metal Products, 10% to Textiles and 9% to the Iron and Steel industry.

Once an industry was selected, establishments in this industry, as well as their upstream suppliers, could take up the subsidy if the average of their last three months' production (employment) was less (equal or less) than the monthly average for the same season a year before. Small- and medium-size establishments meeting these criteria could receive 2/3 of their labor costs (3/4 under special selection) and large establishments could receive 1/2 of their labor costs (2/3 under special selection) while they implemented temporary closures of their business operations.[14]

[13] Japanese Ministry Labor, Employment Security Bureau (1999), p.191.

[14] Note that establishments do not have to pay full wages while they implement temporary business closures. Moreover, the maximum coverage for the establishments in an industry selected under standard selection criteria (*shitei-gyosyu*) was 100 days × the total number of employees, and the maximum coverage for firms in a industry selected under the special selection criteria (*tokutei koyo chosei gyosyu*) was 200 days × the total number of employees. Between July 1995 and October 2000, about 44% of the targeted establishments could apply under the special selection criteria.

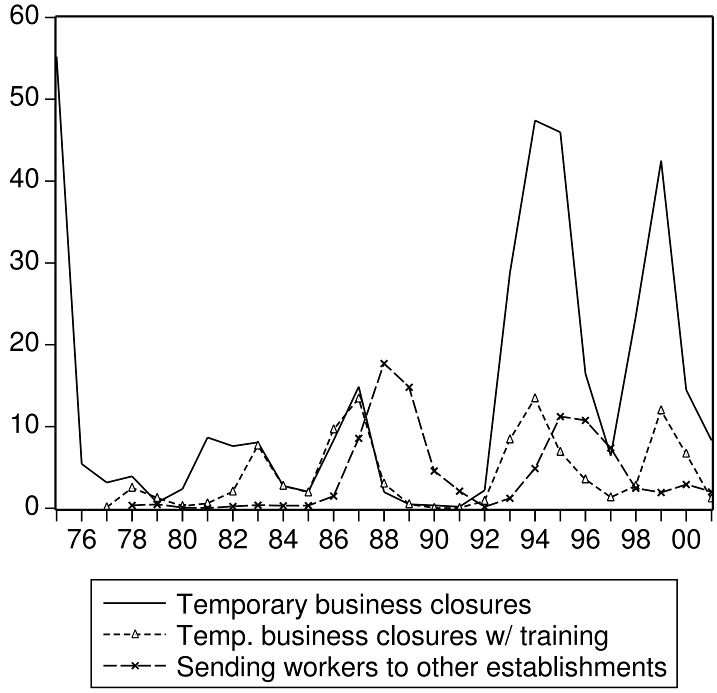


Figure 3.1: Annual total subsidy bill (in billions of yen) by three types of activities for 1975−2001. Data source: the Employment Security Bureau of Japanese Ministry of Health, Labor and Welfare.

Additional allowances of three thousand yen per worker per day were given if establishments provided job training to workers while they temporarily closed their businesses.[15] Instead of business closures, establishments could also send workers to other unrelated establishments for more than three months. In this case, the receiving establishment was required to pay for the labor service provided by the subsidized workers, and the sending establishment paid the difference between the workers' original wage and the amount paid by the receiving establishment. The subsidy covered a fraction of the cost borne by sending establishments.

Although the subsidy program started in 1975, its effect was probably largest during the 1990s, the decade of sluggish growth. Figure (3.1) shows the subsidy bill for each of the three options available to establishments. The total subsidy bill dramatically increased after 1992. Furthermore, among the three options, temporary business closure had the highest share of the total subsidy bill, especially during the 1990s. Subsequently, the analysis of this chapter focuses

[15]In October 2001, however, the allowance for training was reduced to 1200 yen.

on the 1990s for the following reasons: i) more establishments were made eligible during the 1990s, ii) the subsidy rules stabilized by 1990, and iii) data on the subsidy bill by two-digit sector is available only after 1990. In the theoretical section, I will model the policy using the criteria prior to the October 2001 revision.

Table 3.1: Share of subsidy bill by industries for 1990−2002.

| | Total Bill | Annual Average |
|---|---|---|
| Manufacturing Total | 93.96% | 93.45% |
| Food | 0.09% | 0.13% |
| Beverage, Feed and Tobacco | 0.04% | 0.03% |
| Textiles | 5.31% | 4.93% |
| Apparel and Other Textiles | 1.74% | 1.53% |
| Lumber and Wood Products | 0.63% | 0.59% |
| Furniture and Fixtures | 0.64% | 0.59% |
| Pulp and Paper Products | 0.44% | 0.26% |
| Printing and Publishing | 0.03% | 0.03% |
| Chemical and Allied Products | 1.54% | 1.28% |
| Petroleum and Coal Products | 0.15% | 0.15% |
| Plastics | 0.54% | 0.38% |
| Rubber Products | 1.40% | 1.13% |
| Leather, Tanning, Fur Products | 0.19% | 0.17% |
| Ceramic, Stone and Clay Products | 3.98% | 3.52% |
| Iron and Steel | 40.70% | 47.03% |
| Non-ferrous Metals | 1.61% | 1.42% |
| Fabricated Metals | 3.36% | 2.78% |
| General Machinery | 12.75% | 10.49% |
| Electrical Machinery | 6.24% | 7.21% |
| Transportation Equipment | 10.69% | 8.15% |
| Precision Instruments | 1.06% | 0.96% |
| Ordinance | 0.03% | 0.02% |
| Other Manufacturing | 0.80% | 0.67% |
| Other Sector Total | 6.04% | 6.55% |

The share of the total subsidy bill between 1990 and 2002 as well as the annual average share by two-digit sector is provided in Table (3.1).[16] The Iron and Steel industry has the

[16]This data was made available upon request from the Employment Stability Bureau of the Ministry of Health, Labor and Welfare. Unfortunately, the data prior to 1990 is not currently available.

largest annual average share (47.03%), followed by General Machinery (10.49%), Transportation Equipment (8.15%), and Textiles (4.93%).[17] As mentioned previously, the high concentration in the Iron and Steel industry motivates my modeling the effects of the subsidy program on this industry.[18]

### 3.2.2 Overview of the Iron and Steel Industry

This section provides an overview of output, employment and productivity behavior in the Iron and Steel industry between 1973 and 2001. The data set used to study output is the *Japan Industry Productivity Database* (JIP database).[19] This data set was compiled as a part of the Japanese government's project to calculate annual TFP for 84 sectors in Japan between 1973 and 1998.[20] Since the database is based on the 1968 SNA (System of National Account), currently data is available only through 1998. Figure (3.2) shows real gross output between 1973 and 1998. There is a considerable increase in output in the late 1980s and early 1990s, followed by a large drop in the mid- and late-1990s. Figure (3.3) shows the employment trend, taken from the *Employment Trend Survey,* which includes both permanent and temporary workers for all establishments with more than five employees.[21] Except in the mid-1980s, employment exhibits a steady decline since 1973. This, combined with the positive trend in real gross output implies increased capital intensity or TFP during this period.

If subsidized workers are included in employment, then standard productivity measures will

[17]The share calculated is in terms of annual average. The results for the total subsidy bill between 1990 and 2002 are similar.

[18]A strong union presence, which generates wage rigidity and high labor adjustment costs, may be one of the reasons why the Iron and Steel industry has a high take-up rate. However, since eligible industries are given by four-digit industries or subcategories within four-digit industries while the estimated number of subsidized workers are available by two-digit industries, the investigation of the take-up rates across sectors requires the size of eligible workers to be estimated by two-digit industries. This was not done in this paper, and remains an area for future research.

[19]The JIP database is made available in English by Kyoji Fukao on his website: http://www.ier.hit-u.ac.jp/~fukao/english/data/index.html.

[20]See Fukao et al. (2003) for the TFP analysis of the 84 sectors from 1973 to 1998 using the JIP database.

[21]The beginning-of-year (January 1st) figure was used to represent the employment of the previous year.

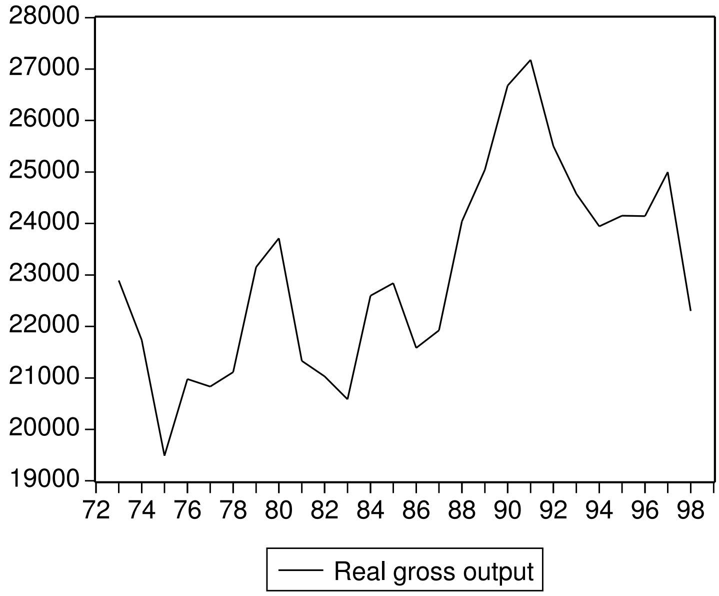


Figure 3.2: Annual real gross output in the Iron and Steel industry (in billions of yen). Data source: JIP database.

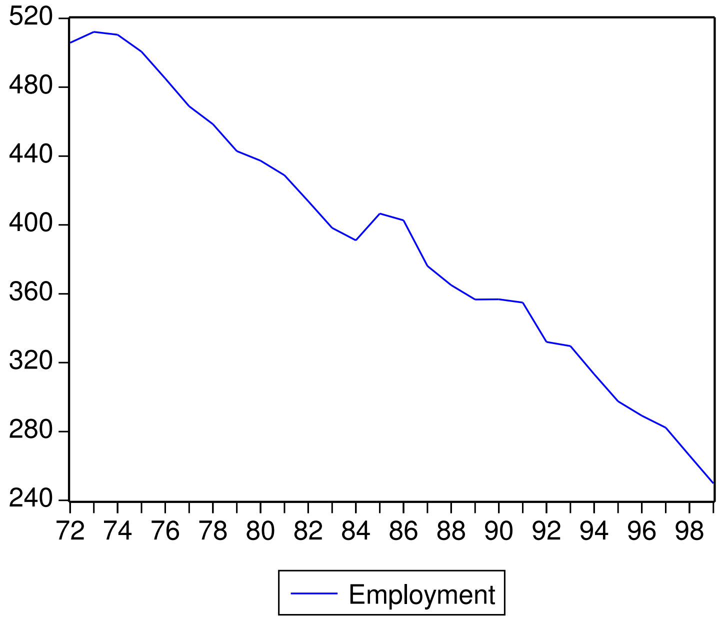


Figure 3.3: Annual employment in the Iron and Steel industry (in thousands), which include both permanent and temporary workers for all establishments with more than five employees. Data source: *Employment Trend Survey.*

be distorted since labor input will be systematically overstated.[22] The data provides the annual subsidy bill by two-digit sector between 1990 and 2002, but does not provide the total number of subsidized work days in each sector. Consequently, we need to estimate the number of unutilized workers for each year using the annual subsidy bill. This was accomplished as follows: first, the average subsidy cost per work-day (i.e. per worker per day) was calculated by dividing the total subsidy bill covering the entire economy by the total number of subsidized work days covered each year.[23] Then the annual subsidy bill for the Iron and Steel industry was divided by the annual average subsidy cost per work-day in order to calculate the total number of subsidized days in this industry. Finally, this number was divided by the annual average work days for workers in the Iron and Steel industry to get an estimate of the number of subsidized workers for each year.[24] Figure (3.4) shows the result of this calculation. On average, 2.1% of Iron and Steel workers were subsidized during this period. In 1995, the highest take-up year, 4.6% of Iron and Steel workers were subsidized.[25]

Since the JIP dataset ends in 1998, an alternative source of output data must be used to calculate productivity between 1990 and 2001. I use measures of real value added as well as capital stock, both based on the 1993 SNA standard, from the *Annual Report on National Account*.[26] An

[22]Note that average work hours may capture part of labor hoarding through the EAS, but it is unlikely to entirely capture the total number of subsidized workers. For the discussion of variable factor utilization in affecting cyclicality of productivity, see Basu and Kimball (1997), Basu and Fernald (2000) and Basu, Fernald and Shapiro (2001).

[23]Since there are three subsidy options (i.e. temporary closures, temporary closures with training, and sending workers to other establishments), the weighted average of these three was taken to estimate the average cost per work-day. Since the work-day cost for sending workers to other establishments cannot be estimated, this was replaced by the work-day cost of temporary closures.

[24]The average work days for workers in the Iron and Steel industry was taken from *Monthly Labor Statistics* by the Japanese Ministry of Health, Labor and Welfare. Since the figure provided here is the monthly average, it was multiplied by 12 to get an approximate annual figure. The data is available at the following website in Japanese: http://stat.jil.go.jp.

[25]However, since the subsidy bill includes the third option, namely 'sending workers to other establishments,' if we focus only on temporary business closures given by the first two options, the estimated fraction of workers should be somewhat smaller than 2.1%.

[26]Capital stock is at completion basis. The data can be found at the following website in Japanese:

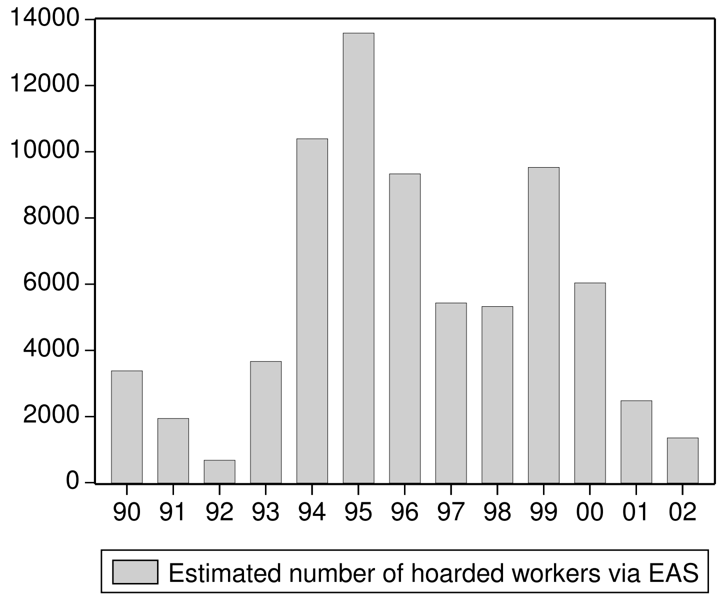


Figure 3.4: Estimated annual number of workers who are unutilized for production via EAS in the Iron and Steel industry. Data source: the information on subsidy was provided by the Employment Security Bureau of the Japanese Ministry of Health, Labor and Welfare. Other data used for the estimation is provided in the text.

annual growth accounting exercise, as in Hayashi and Prescott (2000), was performed to estimate the level as well as the growth rate of TFP both before and after adjusting labor inputs for the number of subsidized workers. More specifically, I adopt the following Cobb-Douglas specification:

$$Y = AK^{\theta}(h \cdot (E - S))^{1-\theta}, \tag{3.1}$$

where $Y$ is real value added, $A$ is the measure of TFP, $K$ is the real capital stock, $h$ is average work hours, $E$ is employment and $S$ is the number of subsidized workers.[27] The cost share of capital $\theta$ is set equal to 0.464, which corresponds to the average cost share of capital excluding material inputs between 1973 and 1998 given by the JIP database.[28]

http://www.esri.cao.go.jp/jp/sna/toukei.html.

[27]The average work hours was taken from *Monthly Labor Statistics* by the Japanese Ministry of Health, Labor and Welfare, and employment data is taken from the *Employment Trend Survey*. Note that the employment figure is based on establishments with more than 5 employees, while the work hour figure is based on establishments with more than 30 employees, due to the lack of series since 1975.

[28]In aggregating the cost share at the two-digit level with the JIP dataset, nominal gross output was used as a weight because the dataset does not provide the total cost for each sector.

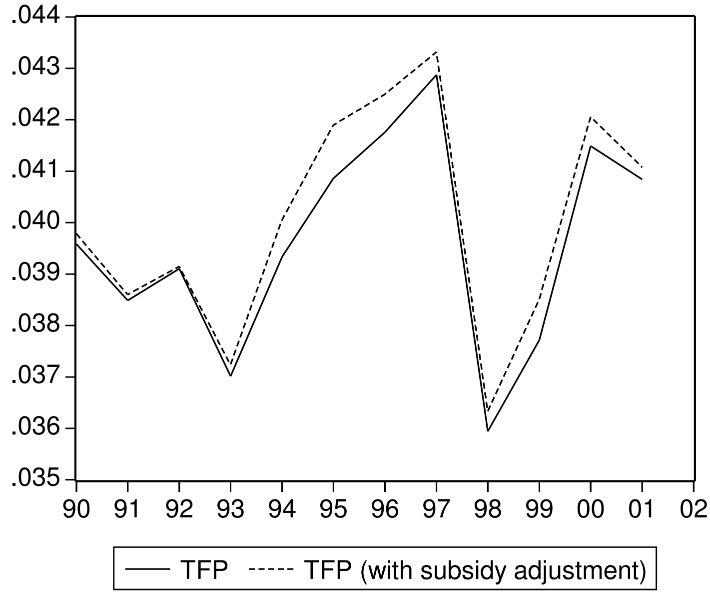


Figure 3.5: TFP (1990−2001) in the Iron and Steel industry. Data source: *Annual Report on National Account* for the output and capital stock, *Employment Trend Survey* for annual employment, and *Monthly Labor Statistics* for average work hours. See the text for the estimated annual number of subsidized workers.

Figure (3.5) shows the level of TFP in the Iron and Steel industry with and without adjustments for the subsidy, using the National Accounts data. The level of TFP is higher when employment is adjusted for the subsidy for obvious reasons. The adjustment is particularly large during the mid-1990s, and on average, adjusted TFP is higher than unadjusted TFP by 1.16% between 1990 and 2001. Figure (3.6) demonstrates the level of TFP using the JIP database. Since the subsidy bill by industry is not available before 1990, the number of subsidized workers prior to 1990 is estimated by applying Iron and Steel's average annual share of 47% between 1990 and 2002 to the total subsidy bill. Except during the 1990s, the two measures of TFP are almost identical.

In the JIP database, the correlation between the log of TFP and the log of real gross output falls from 0.7916 to 0.7843 when the subsidy adjustment is made, and the correlation between the log of TFP and the log of real value added falls from 0.9921 to 0.9906. The correlation between the log of real gross output and the log subsidy bill is −0.645. The result is consistent with the argument that labor hoarding via EAS increases the procyclicality of productivity, although only

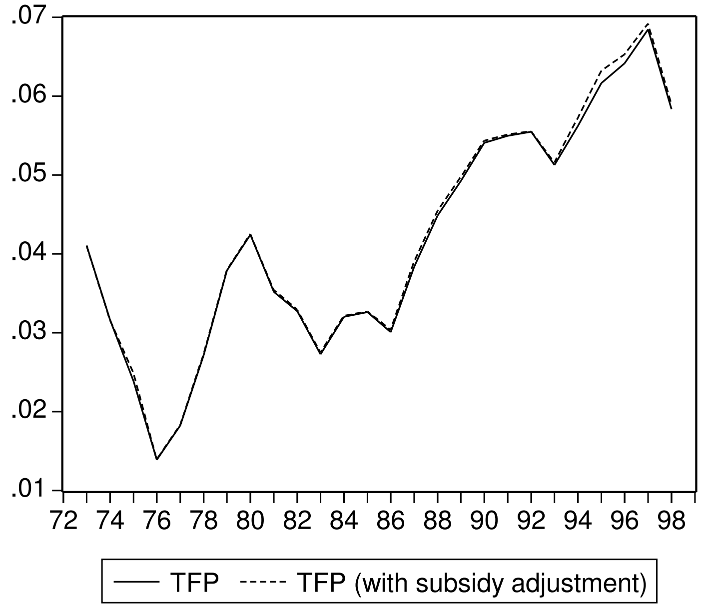


Figure 3.6: TFP (1973−1998) in the Iron and Steel industry. Data source: the JIP database for the output and capital stock, *Employment Trend Survey* for annual employment, and *Monthly Labor Statistics* for average work hours. See the text for the estimated annual number of subsidized workers.

a small part is accounted for by the subsidy.[29]

The exercise in this section reveals that the subsidy, due to the small fraction of subsidized workers, has a trivial impact on the level and procyclicality of TFP. The calibrated model in the next section will attempt to match these moments to investigate the impact of the subsidy program. I will show later that even when the direct impact is small, the EAS can have a significant impact on output and employment volatility.

[29] In terms of growth rate, the correlation between the TFP growth rate and the growth rate of value added falls from 0.9929 to 0.9879. The same exercise using National Accounts data shows that the correlation between the log of TFP and the log of real value added falls from 0.435 to 0.396, and the correlation between the log of real value added and the log of subsidy bill is −0.244. However with this data, significance levels are low due to a small number of observations.

## 3.3 An Industry Model

In this section, I build a simple industry model to capture the effect of the employment subsidy. Let $n_t$ denote the total number of employees in the firm and $e_t \leq n_t$ the number of workers who are utilized for production at period $t$. The firm needs to pay a wage equal to $w$ to each of the $e_t$ workers who actually work and produce, and a fraction $\gamma$ of $w$ to the $n_t - e_t$ workers who are unutilized for production. Firms are eligible for the subsidy with probability $\pi$. If eligible, they can receive payments for their $n_t - e_t$ unutilized workers. Let $s$ denote the fraction of the labor cost of unutilized workers that the government subsidizes. That is, for each unutilized worker, the government pays a fraction $s$ of the discounted wage $\gamma w$ that unutilized workers receive, and the remaining $(1-s)\gamma w$ is paid by the firm. Hence, the total subsidy received by a firm at time $t$ when subsidized is given by $(n_t - e_t)\gamma ws$.[30] Total employment $n_t$ will be the state variable that firms carry to the next period, unless they decide to exit the market.

Firms have a stochastic production function $f(e_t, \varepsilon_t)$, use labor as the only input of production and receive a profitability shock, denoted as $\varepsilon_t$, that has an idiosyncratic component as well as an aggregate component common to all firms. The production function is assumed to be strictly concave in labor and satisfies $f_e > 0$ and $f_{ee} < 0$. Moreover, the wage and price are both assumed to be exogenously determined and invariant over time. For a given price $p$, the expected profits for a firm that employs $n_t$ workers, utilizes $e_t$ workers for production, takes up the subsidy if available, and receives a shock $\varepsilon_t$ at period $t$ are as follows:

$$pf(e_t, \varepsilon_t) - we_t - \gamma w(n_t - e_t) + \chi_t(n_t - e_t)\gamma ws - pc_f - \psi(n_t, n_{t-1}) - \phi(n_t, n_{t-1}). \tag{3.2}$$

The first term is revenue from output. The second and third represent wage payments to utilized and unutilized workers respectively. The fourth captures the subsidy receipts. Here, $\chi_t$ is a random variable that takes a value of 1 with probability $\pi$ and 0 with probability $1-\pi$. The term $pc_f$ reflects the fixed costs of production each period and can be interpreted as the opportunity cost of the entrepreneur. This fixed cost provides firms incentives to exit the market when their

[30] Note that the government provides a guideline on $\gamma$, but the consent of the workers is required (typically through an agreement with their labor union) for them to miss work at a discounted wage $\gamma w$.

prospects look sufficiently unfavorable, instead of simply waiting for their future prospects to turn around. As described in Hopenhayn and Rogerson (1993), this term is necessary for some positive amount of exit to exist in equilibrium. In what follows, $p$ will be set as a numeraire so that it will be omitted from the analysis.

The terms $\psi(n_t,n_{t-1})$ and $\phi(n_t,n_{t-1})$ represent linear hiring and firing costs respectively, and are specified as:

$$\psi(n_t,n_{t-1}) = \tau_h \cdot \max(0, n_t - n_{t-1}) \tag{3.3}$$

$$\phi(n_t,n_{t-1}) = \tau_f \cdot \max(0, n_{t-1} - n_t) \tag{3.4}$$

where $\tau_h$ and $\tau_f$ are the fixed costs of hiring and firing a worker. Either $\tau_h$ or $\tau_f$ must be positive in order to provide firms incentives to take up the subsidy, since without labor adjustment costs, labor adjustment is always instantaneous and there is no need to keep excess workers when firms receive unfavorable shocks.

The timing of decisions is given as follows. An incumbent starts $t$ with previous period's shock $\varepsilon_{t-1}$ and previous period's employment $n_{t-1}$. Before observing its current profitability shock and subsidy eligibility, a firm must decide whether to shut down or stay in business based on its expected profitability. If the firm decides to exit its business, the workers will be dismissed entirely and the firm must pay the firing cost to each of its workers, while avoiding the fixed cost of operation $c_f$.[31] It then receives zero profits in all future periods. If the firm decides to stay, the incumbent firm observes current profitability $\varepsilon_t$ and subsidy eligibility $\chi_t$, and it decides whether to take up the subsidy or not if $\chi_t = 1$. It then chooses employment $n_t$ and the number of utilized workers $e_t$, and produces with $e_t < n_t$ with the subsidy or $e_t \leq n_t$ without the subsidy, before moving to the next period with $n_t$. Here, I do not impose the constraint $e_t = n_t$ when firms are not subsidized, although this equality will hold at an optimum for the set of parameter values provided in the next section.

[31] Alternatively, this implies that at the beginning of the period when the current state is revealed to the firm, it decides whether or not it exits from the market at the end of the period.

The value function for firms under this policy scheme is given by the following equation:

$$V(n_{t-1},\varepsilon_t,\chi_t) = \max_{e_t \le n_t, n_t} \{f(e_t,\varepsilon_t) - we_t - \gamma w(n_t - e_t) + \chi_t(n_t - e_t)\gamma ws - c_f \\ - \psi(n_t,n_{t-1}) - \phi(n_t,n_{t-1}) + \beta\{\max_{\text{stay, exit}}[EV(n_t,\varepsilon_{t+1},\chi_{t+1}), -\phi(0,n_t)]\}\}, \tag{3.5}$$

where $e_t = n_t$ if the firm fully utilizes all its workers. The first order conditions of the value function with respect to $e_t$ and $n_t$ imply that the optimal level of $e_t$ is driven by the current shock $\varepsilon_t$ and parameters such as $s$, $w$, and $\gamma$, while the optimal $n_t$ is affected by $w$, $s$, $\tau_h$, $\tau_f$ and the expected marginal future benefit of the extra worker. This implies that the decision to take up the subsidy will depend not only on the size of the subsidy and labor adjustment costs, but also on how unfavorable today's shock looks relative to future prospects.

For a given set of parameter values, the state variables $n_{t-1}$, $\varepsilon_t$ and $\chi_t$ affect firms' decisions regarding employment (production) and subsidy decisions. First, I will provide a graphical explanation of the state spaces over $n_{t-1}$ and $\varepsilon_t$ for which subsidy take-up takes place given eligibility. Then using the first order conditions, I will show the marginal change that eligibility generates by comparing the behavior of eligible and non-eligible firms facing the same profitability shock and the same level of previous employment, assuming that the eligible firm finds it optimal to take up the subsidy.

Two intuitive implications of the subsidy program are the following. The first is that an increase in the volatility of aggregate and/or idiosyncratic shocks, as well as a reduction in the persistence of shocks, increases subsidy take-up by reducing optimal utilization beneath the optimal level of employment when a firm receives a temporary unfavorable shock. A numerical experiment to examine the impact of increased volatility on the subsidy take-up decision is provided in the appendix. The second is that an eligible firm keeps the level of employment higher, and output lower, in comparison with a non-eligible firm with the same previous level of employment and current profitability conditions.

Regarding the optimal choice of $n_t$, notice that it features a region of inaction owing to the presence of labor adjustment costs. Figure (3.7) illustrates the optimal employment decision rule for a given profitability shock. The dotted diagonal line represents the points where $n_t = n_{t-1}$.

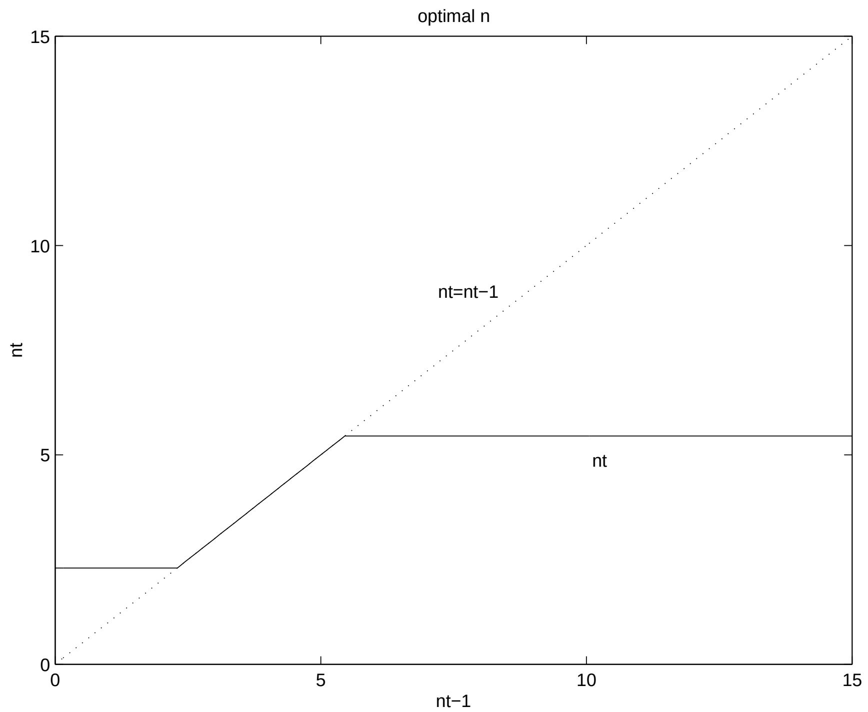


Figure 3.7: Employment decision rule. It shows the optimal choice of employment given the previous level of employment. The diagonal line represents the circumstance in which employment remains the same.

The firm expands in employment size when $n_{t-1}$ is such that the optimal $n_t$ lays above the dotted line, and it contracts if $n_t$ lays below the dotted line. Where the two lines overlap, the figure shows the region of inaction.

On the other hand, the optimal choice of $e_t$ is independent of the state variable $n_{t-1}$. Now, ignoring the constraint $e_t \leq n_t$, consider a case in which a firm receives a temporary favorable shock. In this case, the $e_t$ dictated by the optimal current production decision will be higher than $n_t$ driven by the future prospect of profitability. Therefore, we have an infeasible situation in which $e_t$ is higher than $n_t$, as illustrated by figure (3.8). Obviously, no firm can take up the subsidy under this scenario.

Next consider a case in which a firm experiences a temporary unfavorable shock. Figure (3.9) presents a situation in which $e_t$ lays below $n_t$ for some region of $n_{t-1}$. Note that if firms are small and they wish to expand, they will not take up the subsidy regardless of how unfavorable the shock is. As mentioned before, this is because labor hoarding is costly even when firms receive

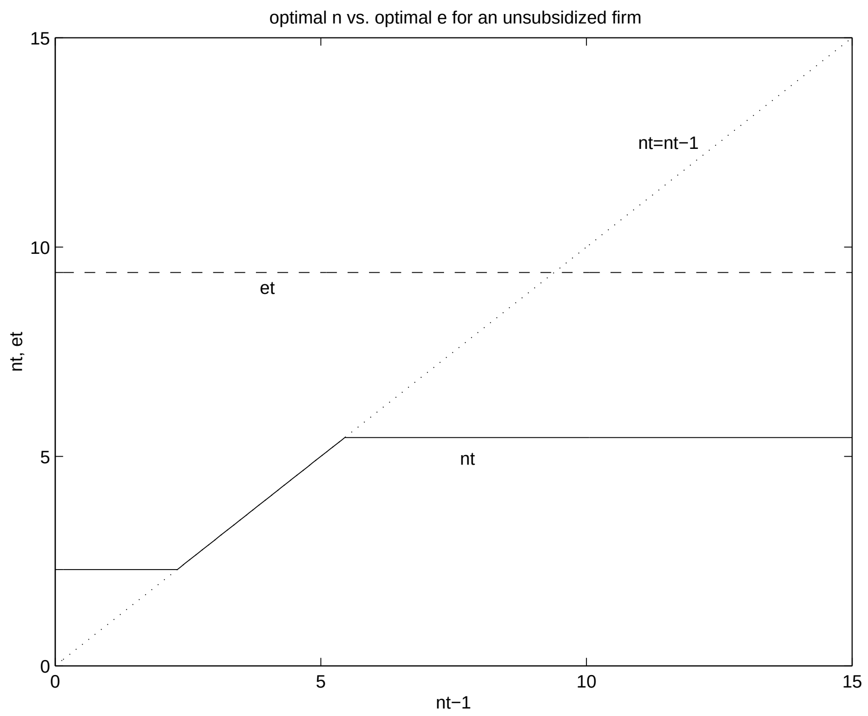


Figure 3.8: Employment and production decision rule for an unsubsidized firm. Since $e_t$ is constrained to be less than $n_t$, this represents the circumstance in which the subsidy take-up does not take place.

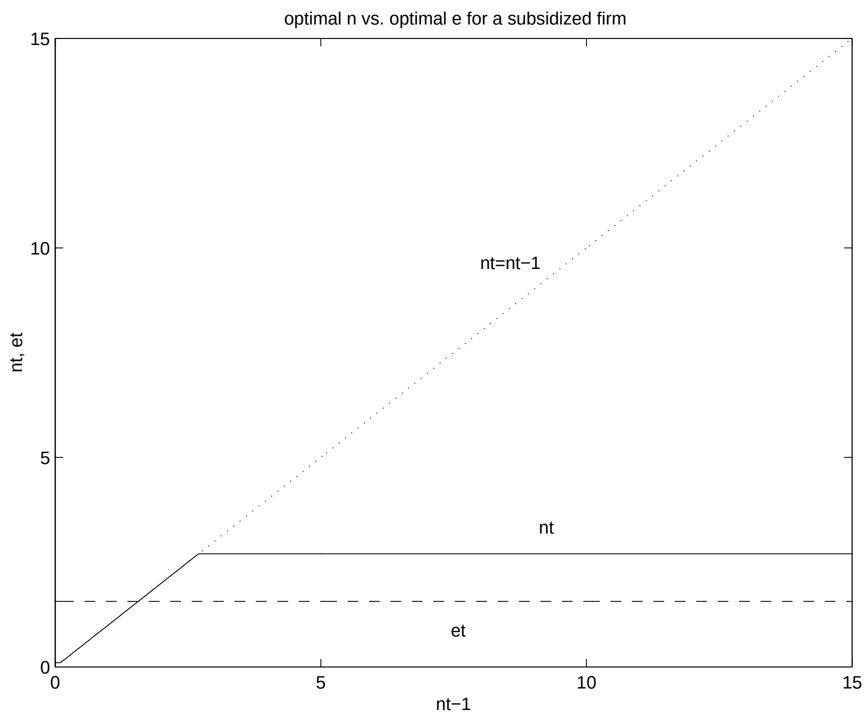


Figure 3.9: Employment and production decision rule for a subsidized firm. Firms apply when the optimally chosen $e_t$ is strictly below $n_t$.

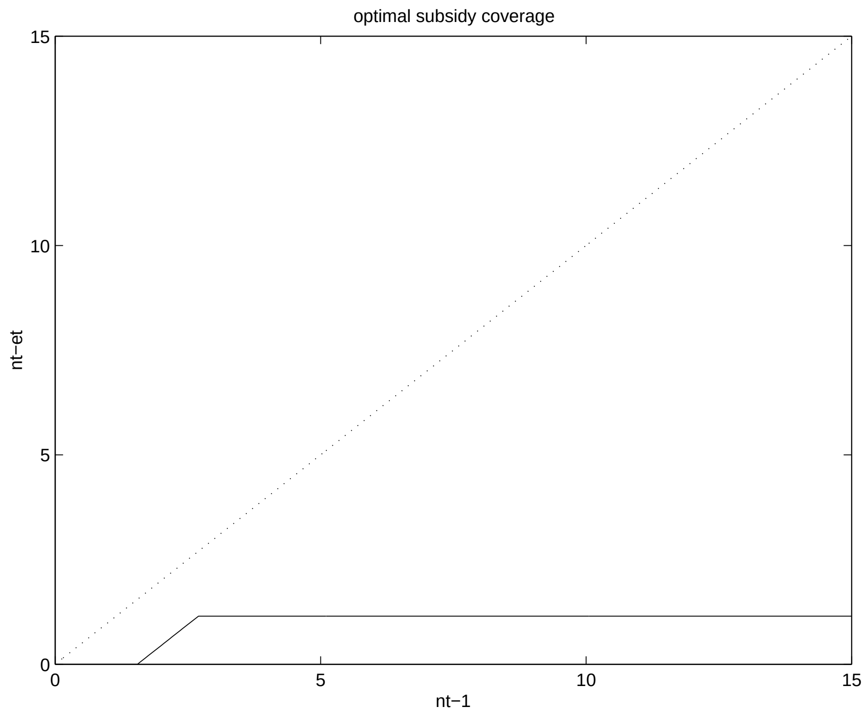


Figure 3.10: Optimal subsidy coverage. This graph shows the distance between $n_t$ and $e_t$ in figure (3.9) for $n_t$ strictly greater than $e_t$.

a subsidy. Therefore, no subsidy take-up takes place when the state variable $n_{t-1}$ is such that the optimal $n_t$ lays above the dotted diagonal line. The optimal subsidy coverage in this case is the difference between $n_t$ and $e_t$ for $n_t < n_{t-1}$. This is presented by figure (3.10). As we can see, the subsidy coverage increases with the state space $n_{t-1}$ within the region of inaction, but stays constant above the region. The distance between the optimal $n_t$ and $e_t$ will increase as the current profitability shock either becomes more unfavorable relative to future prospects, or the current shock becomes highly transitory.

Now, I will illustrate two cases contrasting differences in the behavior of eligible and non-eligible firms in the same values for state variables. As mentioned previously, the purpose of this comparison is to study the marginal change in firm behavior that subsidy eligibility induces. Accordingly, I restrict attention to the portion of the state space of the profitability shocks and the level of employment such that subsidy take-up is optimal contingent on eligibility.[32] The

[32] Subsidy take-up often takes place over the profitability and employment state space in which downsizing is a preferred option for the firms. This does not mean that all downsizing firms take up the subsidy. For example,

behaviors of expanding firms are not discussed since they optimally never take up the subsidy regardless of eligibility. Neither will I discuss the situation where the firm is optimally in a region of inaction regarding employment. Furthermore, I will not focus on the reallocative implications of the subsidy program for the sake of simplicity, and therefore exit decisions are omitted from the analysis for now. Lastly, note that this exercise is not intended to compare behavior with the subsidy program to behavior without the subsidy program. That comparison will be performed using simulations from numerical dynamic programming in the next section.

**Case 3.1** *Firms are eligible for the subsidy*

The program requires that a firm not increase employment when receiving a subsidy. This constraint is not binding in equilibrium since expanding firms are unwilling to bear the labor costs of underutilizing workers.[33] Therefore, subsidized firms naturally have $n_{t-1} \geq n_t > e_t$. Ignoring the region of inaction, the first order conditions of equation 3.5 with respect to $n_t$ and $e_t$ for downsizing firms are:

$$(1-s)\gamma w = \beta EV_n(n_t, \varepsilon_{t+1}, \chi_{t+1}) + \tau_f \tag{3.6}$$

and

$$w - (1-s)\gamma w = f_e(e_t, \varepsilon_t), \tag{3.7}$$

where $EV_n(n_t, \varepsilon_{t+1}, \chi_{t+1})$ is the derivative of $EV(n_t, \varepsilon_{t+1}, \chi_{t+1})$ with respect to $n_t$.[34]

Equation (3.6) shows that the unsubsidized portion of the labor cost of keeping an extra worker, given by the left side of the equation, must be equated with the marginal future benefit of keeping the worker as well as the benefit from avoiding the firing cost today. This provides the optimal condition for $n_t$. Similarly, equation (3.7) shows that the cost of utilizing a worker, given

firms are less likely to apply, the more persistent the sequence of profitability shocks becomes. These cases are not examined as they are irrelevant for the study of the marginal change in firm's behavior with eligibility.

[33]This result may not hold if labor adjustment costs are nonlinear in the number of workers, thereby creating a smoothing incentive for labor adjustment, or if adjustment costs are stochastic.

[34]More specifically, let $\lambda_1$ and $\lambda_2$ be the Lagrange multipliers of constraints $n_{t-1} \geq n_t$ and $n_t > e_t$, respectively. By complementary slackness, $\lambda_2$ must be zero for firms receiving the subsidy. Similarly, $\lambda_1$ must also be zero as we are considering downsizing firms.

by the difference between the wage of a production worker and the cost a firm bears to sustain a worker unutilized, must be equated with the marginal revenue product. This characterizes the optimal condition for $e_t$.

Note that the concavity of $EV$ implies that $EV_n$ is declining in $n_t$.[35] Hence, holding everything else constant, optimal $n_t$ will increase as $s$ approaches one or as $\gamma$ approaches zero. In addition, decreases in $\gamma$ and increases in $s$ or in the probability of being eligible $\pi$ increase $EV$ in the presence of labor adjustment costs. This implies further increases in the optimal $n_t$. On the other hand, the concavity of $f$ implies that the optimal $e_t$ will decrease with $s$ and increase with $\gamma$. Therefore, a higher $s$ or lower $\gamma$, by reducing the costs of unutilized workers, increases the distance between the optimal $n_t$ and $e_t$, thereby resulting in higher subsidy coverage.[36]

Equation (3.6) also implies that, holding $EV$ constant, a higher firing cost $\tau_f$ increases $n_t$. However, this effect is muted since an increase in $\tau_f$ indirectly reduces optimal $n_t$ by reducing $EV$. Hiring costs do not affect $n_t$ directly, as hiring costs already paid are sunk for non-expanding firms. But hiring costs reduce the optimal $n_t$ indirectly by lowering $EV$. This is the intuition given by Hopenhayn and Rogerson (1993): while high firing costs may directly prevent firing, equilibrium employment can still be smaller if high labor adjustment costs substantially reduce profits.

Finally, combining equation (3.6) and equation (3.7), we obtain the following:

$$w - \tau_f = \beta EV_n(n_t, \varepsilon_{t+1}, \chi_{t+1}) + f_e(e_t, \varepsilon_t). \tag{3.8}$$

This implies that when firms are downsizing, they set the expected marginal future benefit of an employed worker, combined with the marginal revenue product of a utilized worker, equal to

[35] Once exit decisions are included in the problem, $EV$ is not always concave in $n_t$. However, $EV$ is still concave over the range of $n_t$ for which firms decide to stay in business.

[36] More formally, consider the case for a downsizing firm (i.e. $\lambda_1 = 0$). The implicit differentiation of equation (3.6) with respect to $n_t$ and $s$ gives $\partial n_t/\partial s = -[\gamma w + \beta(\partial EV_n/\partial s)]/\beta EV_{nn} > 0$ due to the concavity of $EV$ and $\partial EV_n/\partial s > 0$, while the implicit differentiation of equation (3.7) with respect to $e_t$ and $s$ yields $\partial e_t/\partial s = \gamma w/f_{ee} < 0$ due to the concavity of $f$. Similarly, the implicit differentiation of equation (3.6) with respect to $n_t$ and $\gamma$ gives $\partial n_t/\partial \gamma = [(1-s)w - \beta(\partial EV_n/\partial \gamma)]/\beta EV_{nn} < 0$ due to the concavity of $EV$ and $\partial EV_n/\partial \gamma < 0$, while the implicit differentiation of equation (3.7) with respect to $e_t$ and $\gamma$ yields $\partial e_t/\partial \gamma = -(1-s)w/f_{ee} > 0$ due to the concavity of $f$.

the difference between the wage and firing cost. The firing cost is subtracted from wage as it represents the benefit from avoiding a payment that would otherwise be due to the marginal fired worker.[37]

**Case 3.2** *Firms are not eligible for the subsidy*

Next, we will investigate the case for a downsizing firm that is not eligible for the subsidy. As mentioned previously, we still allow for the possibility of not utilizing some of their workers when firms are not eligible, but firms are not required to underutilize their workers. Hence, we have $n_{t-1} \geq n_t \geq e_t$. We maintain the assumption that these constraints do not bind, as we are considering firms that would optimally take up the subsidy if eligible.[38] The first order conditions for this case is given simply by setting $s = 0$ for equations (3.6) and equation (3.7):

$$\gamma w = \beta E V_n(n_t, \varepsilon_{t+1}, \chi_{t+1}) + \tau_f \tag{3.10}$$

and

$$w - \gamma w = f_e(e_t, \varepsilon_t). \tag{3.11}$$

Similarly to equation (3.6), equation (3.10) shows that the labor cost of keeping an extra worker unutilized must be equated with the marginal future benefit of keeping the worker in addition to the firing cost. Moreover, equation (3.7) shows that the cost of utilizing an unutilized worker, given by the difference between the wage and labor hoarding cost, must be equated with the marginal revenue product. Now with the absence of $s$, we can see that the distance between $n_t$ and $e_t$ shrinks faster as $\gamma$ gets closer to one. Hence, higher $\gamma$ reduces the likelihood of a firm idling some

[37]On the other hand, the first order condition for an expanding firm is:

$$w + \tau_h = \beta E V_n(n_t, \varepsilon_{t+1}, \chi_{t+1}) + f_e(n_t, \varepsilon_{t+1}). \tag{3.9}$$

In this case, hiring costs show up as a cost of having an extra worker. Moreover, $n_t = e_t$ holds at an optimum for expanding firms.

[38]As shown later, firms under the described setting choose not to underutilize workers when the subsidy is not available so that $n_t = e_t$ holds at an optimum for non-eligible firms. However, since the value of the Lagrange multiplier (i.e. $\lambda_2$ for $n_t > e_t$) when the constraint binds is expected to be small, as only downsizing firms are considered, it is ignored for the sake of simplicity.

of its workers in the absence of a subsidy, provided that $\tau_f$ is low enough.[39] Again, combining equations (3.10) and (3.11) yields equation (3.8), with $e_t$ replaced by $n_t$ when all workers are utilized.

Comparison between (3.6) and (3.10) reveals $n_t$ given by equation (3.6) (hereafter denoted by $n_t^s$) is strictly higher than the $n_t$ given by equation (3.10) (denoted simply by $n_t$) due to the concavity of $EV$. In addition, $e_t$ given by equation (3.7) (hereafter denoted by $e_t^s$) is strictly smaller than the $e_t$ given by equation (3.11) (denoted simply by $e_t$) due to the concavity of $f$. Hence, for a given profitability shock $\varepsilon_t$, the following condition holds for a downsizing firm that applies for a subsidy when eligible:[40]

$$n_t^s > n_t \geq e_t > e_t^s. \tag{3.12}$$

Hence, an eligible firm keeps the level of employment higher, and output lower, in comparison with a non-eligible firm.

Next, we will study the conditions for positive subsidy take-up with the eligibility, for any given profitability shock. Accordingly, we study the nonstochastic version so that $\varepsilon_t$ will be omitted, and $\chi_t$ is set equal to 1 and will be omitted as well. Now, let $V^s(n_{t-1})$ denote the value function satisfying first order conditions given by equations (3.6) and (3.7) (i.e. $n_t^s$ and $e_t^s$) and $V(n_{t-1})$ denote the value function with the first order conditions given by equations (3.10) and (3.11) (i.e. $n_t$ and $e_t$). Given eligibility, firms will take up the subsidy when $V^s(n_{t-1}) > V(n_{t-1})$.

[39] This is not to say that there is no labor hoarding without subsidy. The change in the intensity of the labor inputs' use is a common practice, but this feature is not modeled in this paper for a simpler exposition of the effects of the policy.

[40] Keep in mind that the condition given by equation (3.12) characterizes the employment and production behavior of subsidized and unsubsidized firms under the same subsidy program with the same $s$ and $\pi$. If we wish to compare the behavior of a firm without the subsidy program ($s = 0$) and a firm with the subsidy program ($s > 0$, $\pi > 0$), we also need to take into account the change in $EV$. In this case, the optimal $n_t$ will be even higher with the subsidy while the optimal $e_t$ remains the same.

That is, the following condition must hold for a subsidy take-up to take place:

$$\underbrace{(n_t^s - e_t^s)s\gamma w}_{\text{total subsidy receipt}} + \underbrace{\tau_f(n_t^s - n_t)}_{\text{savings on firing costs}} + \underbrace{\{\beta[EV(n_t^s) - EV(n_t)]\}}_{\text{change in future value}}$$
$$+ \underbrace{(1-\gamma)w(e_t - e_t^s)}_{\text{reduced wage payments}} > \underbrace{\{f(e_t) - f(e_t^s)\}}_{\text{reduction in revenue}} + \underbrace{\gamma w(n_t^s - n_t)}_{\text{increased employment costs}} . \tag{3.13}$$

The first term on the left side represents the total subsidy received by the firm, the second term shows savings on firing costs with the subsidy, while the third term captures the change in the expected marginal future benefit arising from the different choices of $n_t$, and the fourth term represents the savings on labor costs arising from increasing the number of unutilized workers (i.e. firms pay $\gamma w$ instead of $w$ so that the reduction in payment is $w - \gamma w$ or $(1-\gamma)w$ for each unutilized worker). In contrast, the first term on the right side represents the reduction in revenue associated with reduced production and the second term represents the increase in the cost to the firm for sustaining excess workers through the subsidy program. Notice that with the subsidy, firms benefit from the reduced wage payments at the production worker margin, while firms lose from higher labor costs at the employment margin. Consequently, firms apply when the total benefit exceeds the cost.

As we have previously seen, the first term on the left is only positive for downsizing firms. Next, the second term on the left hand-side and the last term on the right-hand side both involve $n_t^s - n_t$, a term which is positive when a firm applies for the subsidy, according to equation (3.12). Combining these two, the benefit of applying rises relative to the cost as the size of the firing cost, $\tau_f$, increases relative to the cost of sustaining a worker, $\gamma w$, and vice versa. Here, I call this a direct effect of $\tau_f$. The relative sizes of $\tau_f$ and $\gamma w$ also indirectly affects the benefit of the subsidy through the third term on the left side. Equation (3.6) and equation (3.10) show that if $(1-s)\gamma w > \tau_f$, then $EV_n > 0$ for both equations, and in particular, $EV(n_t^s) > EV(n_t)$. On the contrary, if $\gamma w < \tau_f$, then $EV_n < 0$ for both equations and $EV(n_t^s) < EV(n_t)$.[41] That is, when firing costs are very high, the optimal level of $n_t$ is already so high that increasing $n_t$ through the subsidy reduces the expected future value. In the later exercise, we will see that higher firing costs in general

[41]Furthermore, the slope of $EV$ given by equation (3.6) is positive and the slope given by equation (3.10) is negative if $\gamma w > \tau_f > (1-s)\gamma w$. In this case $EV(n_t^s) - EV(n_t)$ can be either positive or negative.

increase subsidy take-up even when $\gamma w < \tau_f$, suggesting that the direct effect dominates.[42]

We now investigate the exit decisions of firms. Firms will decide to exit from the market when the expected loss of staying in the market is greater than the cost of firing its entire workforce (i.e. $EV(n_t, \varepsilon_{t+1}, \chi_{t+1})$ is smaller than $-\phi(0, n_t)$). Since $EV(n_t, \varepsilon_{t+1}, \chi_{t+1})$ considered here is concave and $-\phi(0, n_t)$ is linearly declining in $n_t$, the threshold level of the exit decision will be given by the intersection of $EV(n_t, \varepsilon_{t+1}, \chi_{t+1})$ and $-\phi(0, n_t)$ when they are plotted against $n_t$ while holding everything else constant. That is, the intersection gives the upper bound of $n_t$ below which firms decide to exit for a given $\varepsilon_t$. $EV$ and firing costs are plotted against $n_t$ in figure (3.11). Here, $EV(2)$ corresponds to a higher level of profitability shock compared to $EV(1)$. As the figure shows, no firms with a profitability shock corresponding to $EV(2)$ will exit from the market, while some small firms with a profitability shock corresponding to $EV(1)$ will exit. The subsidy shifts $EV$ up slightly for all $n_{t-1}$, thereby reducing the upper bound of $n_{t-1}$ for exiting. This, combined with the higher employment induced by the subsidy program, reduces the equilibrium amount of exit at the steady-state.

The following strategy was used in order to simplify the numerical dynamic optimization problem given by equation (3.5). We know from equation (3.7) that the unconstrained optimal $e_t$ is static. Accordingly, by using this first order condition, the value function can be reduced to one that involves one choice variable, $n_t$, even when some workers are not utilized. We obtain firm's decision rules regarding the subsidy take-up, $Z(n_{t-1}, \varepsilon_t, \chi_t)$, where $Z = 1$ corresponds to applying for a subsidy and $Z = 0$ corresponds to not applying, by comparing $V^s(n_{t-1}, \varepsilon_t \mid \chi_t = 1)$ with $V(n_{t-1}, \varepsilon_t \mid \chi_t = 1)$ as explained above.

We also obtain the following decision rules by solving the dynamic optimization problem: $X(n_{t-1}, \varepsilon_t, \chi_t)$, where $X = 1$ corresponds to exiting from the market and $X = 0$ corresponds to staying; $N(n_{t-1}, \varepsilon_t, \chi_t)$, which gives the optimal choice of employment; and $E(n_{t-1}, \varepsilon_t, \chi_t)$, which provides the optimally chosen level of production at time $t$. Furthermore, whenever $Z = 1$, a fraction $\pi$ of firms follow the decision rules obtained from solving the value function with subsidy

[42]The size of hiring costs $\tau_h$, on the other hand, only has an indirect effect through the third term on the left by affecting $EV$.

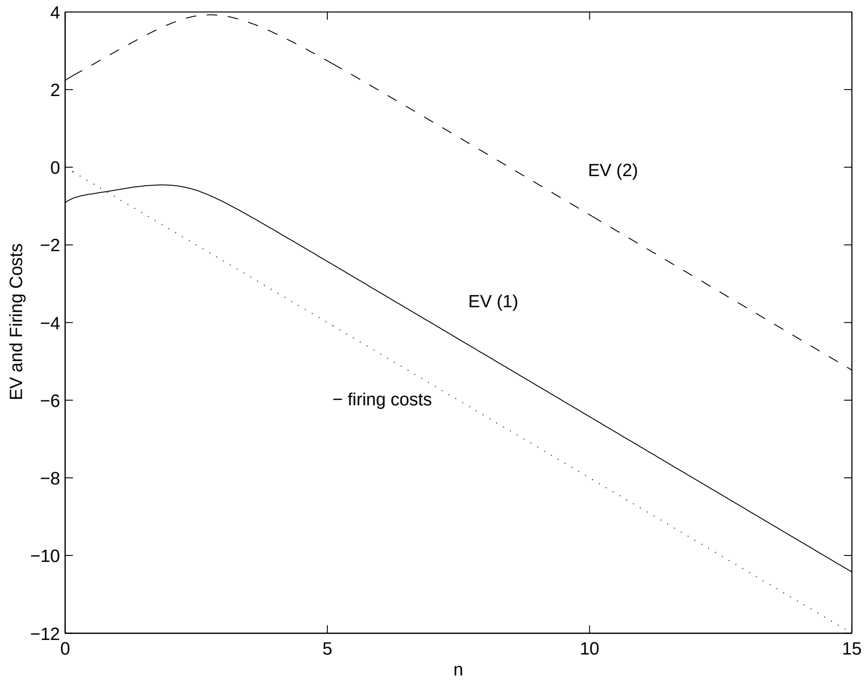


Figure 3.11: $EV$ vs. firing costs. Firms decide to exit from the market when the expected loss of staying in the market is greater than the cost of firing its entire workforce. $EV(2)$ corresponds to a higher level of profitability shock compared to $EV(1)$.

while the remaining fraction $1 - \pi$ of firms follow the decision rules implied by the value function without subsidy. On the other hand, when $Z = 0$, all firms follow the decision rules obtained from solving the value function for $\chi_t = 0$. The decision rule regarding the optimal number of utilized workers, $E(n_{t-1}, \varepsilon_t, \chi_t)$, is obtained according to the firm's subsidy take-up decisions. Here again, a fraction $1 - \pi$ of firms follow the decision rules given by the value function without subsidy even when they wish to apply.

From the solutions above, we obtain a stationary distribution over the employment and profitability shock pairs for a given level of entry $M$. This in turn will provide us the rates of entry, exit, job reallocation, average employment, average output and average productivity in a stationary equilibrium. Furthermore, a mass of size $M$ new entrants are added each period in obtaining a stationary distribution through contraction mapping. Following Hopenhayn and Rogerson (1993), the starting level of profitability shock (or put differently, initial luck of the draw) for an entrant is taken from the uniform distribution, and all entrants start at zero employment.

The boundaries of this uniform distribution are set by the condition of the discretization of the AR(1) idiosyncratic profitability shock process explained in the following section.[43] After the initial profitability shock, entrants evolve just as incumbents. Furthermore, entering firms are assumed not to receive a subsidy with their first production, and they must produce at least once before exiting from the market.

Denoting $\lambda_t$ as a vector which describes the distribution over the entire set of employment levels and profitability shocks at period $t$, and $T(\lambda_t, M)$ as the transition matrix that maps the state at time $t$ to the next state period given firms' decision rules, the state transition equation is given by $\lambda_{t+1} = T(\lambda_t, M)$. Accordingly, the time stationary distribution is described as a vector $\widehat{\lambda}$ such that $\widehat{\lambda} = T(\widehat{\lambda}, M)$. This distribution provides us with steady-state average employment in the economy. Moreover, the stationary distribution over production-profitability shock pair can be constructed from $\widehat{\lambda}$, by moving the corresponding fraction of firms to the optimally chosen level of production given by the first order condition of $e$, obtained from equation (3.7) for each level of shock, whenever their optimal employment exceeds the optimal number of utilized workers. This distribution, in turn, provides us with the steady-state level of average production in the economy.

Because the growth rate of the industry is held constant in equilibrium, the number of the firms that exit the market must be offset by the number of firms that enter the market $M$. Hence, the analysis is one in which there is no net entry, as exit and entry rates are identical in the steady-state. This simplification also follows Hopenhayn and Rogerson (1993). Since total employment is held constant in equilibrium, the number of jobs destroyed by incumbents and exiting firms have to be matched by the amount of jobs created by the incumbents and entering firms.

Finally, the operator $T$ is homogeneous of degree one in $\widehat{\lambda}$ and $M$. Consequently, the rate of entry (and therefore the rate of exit) remains constant regardless of the size of $M$, as doubling $M$ also doubles the total number of firms in a stationary equilibrium. Accordingly, choosing a

[43] As explained in the next section, the upper bound and the lower bound are set at three standard deviations away from the mean, and the state space of idiosyncratic profitability shock is discretized into forty states. The use of an uniform distribution was preferred over that of a stationary or normal distribution, since these distributions would reduce the steady state rate of exit (and therefore entry) by reducing the number of firms that start off poorly.

particular level of $M$ corresponds to choosing a particular measure of firms and the total amount of employment in a stationary equilibrium, while statistics such as average employment, average output and productivity and the rates of job creation and destruction are unaffected by the choice of $M$. Although a positive subsidy can potentially affect the total number of firms through $M$ by raising the expected value of starting a business, $M$ has not yet been endogenized in this model. In the following section, the equilibrium amount of entry $M$ is simply set so that the total number of firms in equilibrium are the same for the subsidy case with $s > 0$ and the benchmark case with $s = 0$.

## 3.4 Results

### 3.4.1 Basic Setup and Calibration

To find an equilibrium via numerical dynamic programming, I begin by specifying the production function as:

$$f(e_t, \varepsilon_t) = \varepsilon_t \cdot e_t^{\theta} \text{ where } 0 < \theta < 1. \tag{3.14}$$

The path for the profitability shocks $\varepsilon_t$ is given as follows:

$$\varepsilon_t = \alpha_t + u_t, \tag{3.15}$$

and

$$\alpha_t = \left\{ \begin{array}{c} \alpha_g \text{ with prob. } \delta \text{ if } \alpha_{t-1} = \alpha_g \\ \alpha_b \text{ with prob. } 1-\delta \text{ if } \alpha_{t-1} = \alpha_g \\ \alpha_g \text{ with prob. } 1-\delta \text{ if } \alpha_{t-1} = \alpha_b \\ \alpha_b \text{ with prob. } \delta \text{ if } \alpha_{t-1} = \alpha_b \end{array} \right\} \text{ where } \alpha_g > \alpha_b > 0 \tag{3.16}$$

and

$$u_t = \rho u_{t-1} + v_t \text{ where } 0 < \rho < 1 \text{ and } v_t \sim i.i.d. \text{ with } E[v_t] = 0. \tag{3.17}$$

Here, $\alpha_t$ represents the aggregate state. It follows a two-state Markov process with symmetric transition probability $\delta$. Although actual business cycles arguably display asymmetric transition probabilities with the good state being longer than the bad state, a symmetric probability was used to reflect the longer than usual downturn experienced by the Japanese economy during the 1990s.[44] Meanwhile, $u_t$ captures the idiosyncratic profitability shock, which follows an AR(1) process. The parameter $\rho$ is the persistence of idiosyncratic shocks that firms receive each period, and $v_t$ is a Gaussian white noise process with the standard deviation $\sigma_v$. For a given level of persistence $\rho$ and the standard deviation $\sigma_v$, a corresponding forty-state Markov transition matrix and state vector for idiosyncratic shocks were created to approximate the AR(1) process for each level of $\alpha$. Further, for each aggregate state, the upper and lower bounds of the shock are set at three standard deviations of $u_t$ away from $\alpha_g$ and $\alpha_b$. Note that forty idiosyncratic states combined with two aggregate states yields a total of eighty profitability states.

The profitability shocks can be interpreted as technology shocks or as demand shocks since $\varepsilon_t$ will be multiplied by the price level $p$ which is normalized to one. Here, we do not consider the distinction between supply and demand shocks, and simply regard $\varepsilon_t$ as profitability shocks. Furthermore, note that the steady state statistics in section (3.4.2), computed analytically by the stationary distributions, refer to the average figures of both aggregate states. Alternatively, the steady state statistics for a good aggregate state and a bad state can be computed separately. However, the average statistics were used in order to measure the long-run impact of the subsidy. The second moment properties of the subsidy in terms of the volatility of employment, productivity and output (i.e. fluctuation around the long-run mean) are examined via simulation in section (3.4.3), instead of using an analytical computation.

Key parameters used to solve the model are summarized in Table (3.2). Since subsidy data is only available annually, the time interval is set to one year. Moreover, the focus of the exercise will be the 1990s, during which the subsidy bill increased and data by two-digit sector is available. The wage is normalized to one, and both hiring and firing costs are set equal to 80% of the annual wage.[45] Later, we will examine the impact of higher adjustment costs by setting both hiring and

[44] The asymmetric transition probability reduces the steady-state fraction of subsidized workers and makes it more difficult to match with the description of the data during the 1990s.

[45] Although the price is also normalized to one in the model, it is allowed to fluctuate relative to the wage as it is multiplied by a profitability shock.

Table 3.2: Parameter values used to obtain stationary distributions with annual frequency.

| | |
|---|---|
| $w = 1$ | wage |
| $\tau_h = 0.8$ | hiring costs |
| $\tau_f = 0.8$ | firing costs |
| $c_f = 2$ | fixed cost of operation |
| $r = 0.04$ | interest rate |
| $\beta = (1/(1+r)) = 0.96$ | discount rate |
| $\gamma = 0.8$ | fraction of wage paid to unutilized workers |
| $\pi = 0.5$ | prob. of being eligible for the subsidy |
| $s = 2/3$ | subsidy coverage |
| $\theta = 0.55$ | labor share of total cost |
| $\rho = 0.75$ | persistence of idiosyncratic shocks |
| $\sigma_v = 0.5$ | standard deviation of $v_t$ |
| $\alpha_g = 3.13$ | mean profitability of good state |
| $\alpha_b = 2.27$ | mean profitability of bad state |
| $\delta = 0.6$ | aggregate state transition probability |

firing costs equal to the annual wage. The fixed cost of operation (or entrepreneur's opportunity cost) is set to twice the wage. The annual interest rate is set equal to 4%. This figure corresponds to the government financial institutions' key lending rate to small- and medium- size enterprizes averaged in the 1990s.[46]

The EAS provides a guideline on the fraction of wages that firms should pay to subsidized workers, and it does not require that subsidized workers be paid the full amount. Accordingly, payment to unutilized workers is set equal to 80% of the wage. This number was estimated by combining three figures: the annual salary of manufacturing workers, taken from the *Basic Survey on Wage Structure*; the average work-days of the manufacturing sector, provided by the *Monthly Labor Statistics*; and the average subsidy cost per worker per day as described in section (3.2.2).[47] The estimated subsidy cost per person per day is about 42% of the average basic wage between

[46]The interest rate data is available at the Bank of Japan's website in Japanese: http://www.boj.or.jp/stat/dlong_f.htm.

[47]Both the *Basic Survey on Wage Structure* and the *Monthly Labor Statistics* are published by the Ministry of Labor (current Ministry of Health, Labor and Welfare). The data used in the paper is posted on the website of the Japan Institute of Labor Policy and Training in Japanese: http://stat.jil.go.jp.

1985 and 2001. This implies that if $s = 1/2$, $\gamma = 0.94$ (or $\gamma = 0.84$ if instead of the basic wage, the actual wage which includes overtime is used) and if $s = 2/3$, $\gamma = 0.71$ (or $\gamma = 0.63$ if the actual wage is used).[48] The parameter value is set around the mid-point at $\gamma = 0.8$.

The probability of being eligible for the subsidy program each year is set equal to 50%. This seems reasonable given the high concentration of subsidies in the Iron and Steel industry during the 1990s.[49] The subsidy coverage is set equal to 2/3 of the wage paid to unutilized workers. The parameter $\theta$, which equals the labor's share of total cost, is set to 0.55; this figure corresponds to the average cost share of labor (excluding intermediate inputs) between 1973 and 1998 given by the JIP database.

The persistence of the shock is set equal to 0.75, and the standard deviation of $v_t$ is set equal to 0.5.[50] The mean profitability shock in the bad state ($\alpha_b$) is set at 2.27, so that the lowest shock in a bad state takes a positive value, and the distance between $\alpha_g$ and $\alpha_b$ is set slightly above one standard deviation of idiosyncratic shocks.[51] Here, $\alpha_g$ is set at 3.13. The probability that the aggregate state persists ($\delta$) is equal to 0.6. These parameter values are assigned to generate realistic statistical properties of key variables such as the fraction of subsidized workers, job creation and destruction rates, and entry and exit rates. Employment was discretized in 301 grid points ranging from zero to fifteen; the upper bound was set to guarantee that it exceeds equilibrium employment with the highest value of the profitability shock.

Average productivity is defined as total output divided by total employment. More specifically, using $\widehat{\lambda}(n_i, \varepsilon_j)$ and $\widehat{\lambda}(e_i, \varepsilon_j)$ to represent the proportion of firms over each $(n_i, \varepsilon_j)$ and $(e_i, \varepsilon_j)$

[48]Since the estimated subsidy cost per work-day is not available by two-digit sectors, these estimates are for the entire manufacturing sector.

[49]Unfortunately, information on the fraction of firms covered by the subsidy is not currently available.

[50]These two combined implies that the standard deviation of the idiosyncratic shock is about 0.756 since $\sigma_u = \sqrt{\sigma_v^2/(1-\rho^2)}$.

[51]With $\alpha_b = 2.27$, the lowest value of $\varepsilon_t$ is 0.002.

pairs in a stationary equilibrium, the average productivity is defined as:

$$
\begin{aligned}
\text{Average productivity} &= \frac{\text{Total Output}}{\text{Total Employment}} \\
&= \sum_{\varepsilon_j}\sum_{e_i}\sum_{n_i}\left(\frac{n_i \cdot \widehat{\lambda}(n_i,\varepsilon_j)}{\sum_{\varepsilon_j}\sum_{n_i} n_i \cdot \widehat{\lambda}(n_i,\varepsilon_j)}\right)\left(\frac{f(n_i,\varepsilon_j)}{n_i}\right)\cdot \xi, \\
&\text{where } \xi = \left(\frac{\widehat{\lambda}(e_i,\varepsilon_j)\cdot f(e_i,\varepsilon_j)}{\widehat{\lambda}(n_i,\varepsilon_j)\cdot f(n_i,\varepsilon_j)}\right). \qquad (3.18)
\end{aligned}
$$

The term in the first bracket shows the relative share of employment in each $(n_{i,}\varepsilon_j)$ pair of the stationary distribution, and the second term reflects output per worker when $n_i$ workers are used for production. $\xi$ is the ratio of the actual output to the output which would have been realized if $n_i$ workers were used instead of $e_i$. This ratio is strictly less than one when some workers are unutilized. The products of these terms are summed over the entire range of employment and shocks to obtain average productivity. Notice that this definition includes subsidized workers, who produce zero output, in calculating the productivity.

I also present a productivity measure adjusted for hiring and firing costs and the subsidy cost per worker. This measure controls for the gain associated with having to spend less resources in hiring and firing with the subsidy, as well as the associated loss in the form of a higher government deficit and/or higher tax. The calculation is done simply by subtracting the hiring and firing costs per worker as well as the cost of the subsidy per worker from average productivity as defined by equation (3.18). However, this should not be interpreted as a welfare measure, as we have not modeled the utility benefit of the subsidy for workers nor the gains associated with sustaining better job-worker matches for experienced workers.

Average productivity is alternatively defined as total output divided by the total number of utilized workers:

$$
\begin{aligned}
\underset{\text{(based on utilized workers)}}{\text{Average productivity}} &= \frac{\text{Total Output}}{\text{Total Number of Utilized Workers}} \\
&= \sum_{\varepsilon_j}\sum_{e_i}\left(\frac{e_i \cdot \widehat{\lambda}(e_i,\varepsilon_j)}{\sum_{\varepsilon_j}\sum_{e_i} e_i \cdot \widehat{\lambda}(e_i,\varepsilon_j)}\right)\left(\frac{f(e_i,\varepsilon_j)}{e_i}\right). \qquad (3.19)
\end{aligned}
$$

Obviously, this definition excludes unutilized workers. Hence, comparing equation (3.18) and equation (3.19) for the same level of subsidy coverage $s$ captures the direct effect of hoarding on average productivity. More specifically, the ratio of productivity based on employment to productivity based on utilized workers (both when $s = 2/3$) shows a reduction in productivity as a direct result of labor hoarding (i.e. the ratio of productivity calculated using equation (3.18) to that given by equation (3.19)). Since this figure is equivalent to the ratio of the total number of utilized workers to total employment, one minus this ratio matches the fraction of subsidized workers.

Finally, the steady-state rate of job turnover is the ratio of the total number of jobs destroyed by incumbents and exiting firms to total employment at the steady-state. Since total employment stays constant in a stationary equilibrium, this figure obviously equals the steady-state rate of job creation, which is the ratio of the jobs created by both incumbents and entrants to total employment at the steady-state. These measures allow us to evaluate the magnitude of total job reallocation occurring in the economy.

### 3.4.2 Stationary Distribution

This section examines the properties of stationary distribution. In order to examine the effects of subsidies on productivity, the benchmark model sets $s = 0$ while the subsidy case sets $s = 2/3$. First, I investigate a case without volatility in aggregate shocks. The value of $\alpha$ in this exercise is set equal to 2.7. Then I will add volatility in $\alpha$, while preserving the mean, as specified in the previous section. Finally, I will increase the hiring and firing costs from 80% of the wage to 100% to investigate the impact of this change. As mentioned previously, the profitability shocks are parameterized to generate realistic values for the fraction of subsidized workers, the rates of entry and exit, and the rates of job creation and destruction.

Although studies on annual rates of entry, exit, job creation, and destruction in Japan are not extensive, due to a lack of data comparable to the LRD for American manufacturing establishments, Motonishi and Tachibanaki (1999) attempt to estimate these figures by using the establishment level data for 1988, 1990 and 1993 from *Census of Manufacturers* compiled by the Japanese Ministry of Economy, Trade and Industry. The rate of entry (exit) on an annualized basis is 8.74% (7.91%) for the Iron and Steel industry for 1988−1990, and 5.68% (8.15%) for 1990−1993.[52] Motonishi and Tachibanaki also provide the rate of job creation and destruction (adjusted on an annualized basis) during these periods.[53] The rate of job creation (destruction) on an annualized basis provided by this study is 4.55% (4.81%) for the Iron and Steel industry for 1988−1990, and 2.91% (4.83%) for 1990−1993.

In this exercise, the number of entrants $M$ is set so that the total number of firms is equal to one in both cases. As mentioned before, increasing $M$ increases the total number of firms, and therefore total employment and output proportionally, but average size as well as average firm output remains the same. Here, I assume that the impact of the subsidy on $M$ is trivial. Moreover, the values for the average size of firms (or total employment), average output by firm (or total output) and average productivity obtained for the subsidy case are normalized by the corresponding benchmark values to facilitate comparison, and for this reason these benchmark values are set equal to one.

The key statistics given by the stationary distributions without aggregate volatility are summarized in Table (3.3). Overall the changes are small. The fraction of subsidized workers generated by the stationary distribution is 0.36%. The exit rate drops from 4.96% to 4.86% with the subsidy, while the job turnover rate falls from 3.83% to 3.78%. Average firm size is 0.14% higher and average firm level output is 0.15% lower. The reduction in output in spite of higher employment is caused by the presence of unutilized workers.

Average productivity falls by about 0.29% with the subsidy program. When average pro-

[52] While this data includes all manufacturing establishments with more than 4 employees, it does not include firms that have entered and exited between census years. As a result, the figures on entry and exit rates presented in this study (which are adjusted on an annualized basis) may underestimate the true magnitude of entry and exit.

[53] Again, the annual rates of job flows may be underestimated since firms that enter and exit between the census years are not included. Furthermore, employment volatility during the census years could potentially generate smaller figures for both job creation and destruction rates when calculated on an annualized basis than the actual annual job creation and destruction rates (i.e. if a firm hires 100 new employees in 1990 and fires 100 in 1993, this firm's employment stays constant over the 1990 and 1993 census). GDP growth rates fluctuate slightly between 1988−1990, but follow a steady decline for 1990−1993, so that the underestimation arising from employment volatility is potentially less for the latter interval.

Table 3.3: Summary statistics of stationary distributions without aggregate volatility: $\alpha = 2.7$.

| | s = 0 | s = 2/3 |
|---|---|---|
| Fraction of workers covered by the subsidy | 0.0000 | 0.0036 |
| Exit rate | 0.0496 | 0.0486 |
| Job turnover rate | 0.0383 | 0.0378 |
| | | |
| Total number of firms | 1.0000 | 1.0000 |
| Average firm level employment | 1.0000 | 1.0014 |
| Average firm level output | 1.0000 | 0.9985 |
| | | |
| Average productivity based on employment | 1.0000 | 0.9971 |
| — adjusted for hiring and firing costs | 1.0000 | 0.9974 |
| — adjusted for hiring, firing and subsidy costs | 1.0000 | 0.9961 |
| Average productivity based on utilized workers | 1.0000 | 1.0007 |

ductivity is calculated based on utilized workers, it increases slightly by 0.07%. This gain is generated by the increased flexibility of production decisions via the subsidy program: under the benchmark case without subsidy, firms hold some excess workers who are used for production due to the presence of labor adjustment costs. While firms hold even more excess workers with the subsidy program, these workers are not used for production, thereby increasing productivity when calculated only in terms of utilized workers.

Here, the drop in productivity due to labor hoarding, which corresponds to the size of subsidized workers, is 0.36%. In addition, when average productivity is adjusted for labor adjustment costs, the negative impact of the subsidy on productivity shrinks, reflecting the fact that the subsidy helps firms avoid labor adjustment costs. However, when we further control for the cost of the subsidy, average productivity falls slightly further in comparison with the benchmark value, indicating that the cost of the subsidy is higher than savings on labor adjustment costs.

Now we add aggregate volatility without changing the mean $\alpha$, while keeping hiring and firing costs at 0.8. The results are presented in Table (3.4). The fraction of subsidized workers generated by the stationary distribution now increases to 1.28%. As expected, this implies that volatility increases subsidy take-up. Since the estimated annual average fraction of subsidized workers in the Iron and Steel industry is 2.1%, the model does not exaggerate the extent of subsidy coverage. The model's exit rate is 4.89% when the subsidy is set equal to zero, and it drops to 4.73% when the subsidy is set equal to two-thirds of payments to unutilized workers. The job turnover rate falls from 4.05% to 3.91% when the subsidy program is in place. Compared with the "no aggregate volatility" case, the drop in both the exit rate and the job turnover rate is slightly bigger with volatility. This may be due to the fact that the subsidy's benefit increases with higher aggregate volatility, thereby raising $EV$.

Table 3.4: Summary statistics of stationary distributions with aggregate volatility: $\alpha_g = 3.13$, $\alpha_b = 2.27$.

| | Low adj. costs | | High adj. costs | |
|---|---|---|---|---|
| | $\tau_h = 1 = \tau_f = 0.8$ | | $\tau_h = 1 = \tau_f = 1$ | |
| | $s = 0$ | $s = 2/3$ | $s = 0$ | $s = 2/3$ |
| Fraction of workers covered by the subsidy | 0.0000 | 0.0128 | 0.0000 | 0.0157 |
| Exit rate | 0.0489 | 0.0473 | 0.0508 | 0.0484 |
| Job turnover rate | 0.0405 | 0.0391 | 0.0369 | 0.0343 |
| | | | | |
| Total number of firms | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Average firm level employment | 1.0000 | 1.0096 | 1.0000 | 1.0187 |
| Average firm level output | 1.0000 | 0.9982 | 1.0000 | 1.0015 |
| | | | | |
| Average productivity based on employment | 1.0000 | 0.9887 | 1.0000 | 0.9831 |
| — adjusted for hiring and firing costs | 1.0000 | 0.9895 | 1.0000 | 0.9851 |
| — adjusted for hiring, firing and subsidy costs | 1.0000 | 0.9850 | 1.0000 | 0.9796 |
| Average productivity based on utilized workers | 1.0000 | 1.0016 | 1.0000 | 0.9988 |

Similar to the "no aggregate volatility" case, average firm level employment goes up with the subsidy while average firm level output drops. Again, higher average employment does not lead to higher average output at the firm level, due to the presence of subsidized workers. Average productivity based on employment, given by equation (3.18), falls about 1.13% with the subsidy. As before, average productivity based on utilized workers goes up by 0.16% due to the flexibility of production decisions with the subsidy. The sum of these two measures approximately corresponds to the drop in productivity as a direct result of labor hoarding. Again, average productivity falls

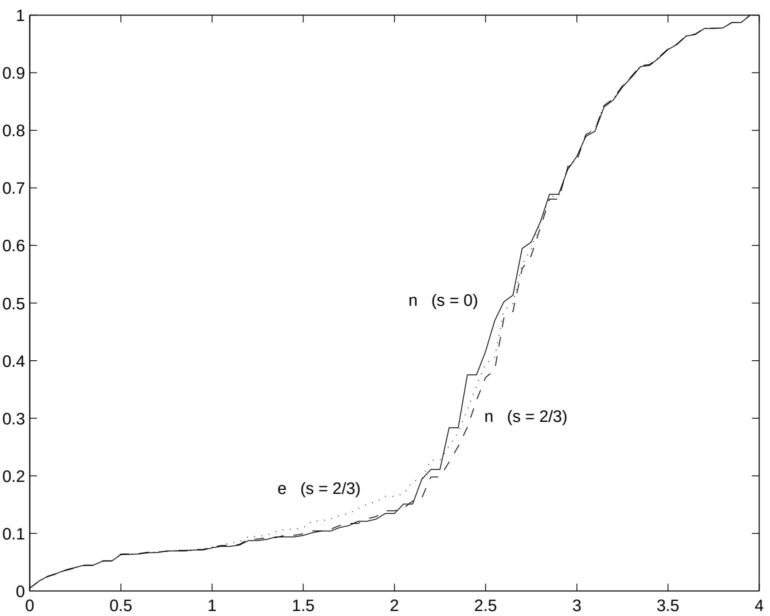


Figure 3.12: Cumulative distribution functions of three stationary distributions. The solid line shows the cdf of firm level employment when the subsidy is set equal to zero. The dashed line shows the cdf of employment when the subsidy is set equal to 2/3 of wage. The dotted line shows the stationary distribution in terms of utilized workers when subsidy is set equal to 2/3 of wage.

even further after controlling for labor adjustment and subsidy costs.

The drop in productivity due to labor hoarding generated by this model is quite successful in approximating the impact of labor hoarding in the data as described in section (3.2.2). Namely, the adjusted TFP (i.e. average productivity based on utilized workers) is higher than unadjusted TFP (average productivity based on employment) by about 1.2% in the data between 1990 and 2001. However, in the growth accounting exercise, the drop in TFP is smaller than the fraction of subsidized workers, as only the labor share of total cost applies to the overall reduction in productivity.[54]

Figure (3.12) provides cumulative distribution functions of three stationary distributions: a stationary distribution over employment for all levels of idiosyncratic and aggregate shocks when

[54] Although the Iron and Steel sector went through a process of substitution from labor towards capital over the last couple of decades, the intensity of capital usage and labor are likely to be complementary over a much shorter horizon (i.e. a year or less). This short-run complementarity assures that the correlation between capital usage and labor is high at the high frequency, and therefore, introducing capital should not undermine the result given by the model.

$s = 0$; a stationary distribution over employment for all levels of idiosyncratic and aggregate shocks when $s = 2/3$; and finally a stationary distribution over utilized workers for all levels of idiosyncratic and aggregate shocks when $s = 2/3$. Note that the distributions are bumpy since the state spaces (employment and profitability) are discontinuous. The figure confirms that the average firm level employment is higher when the subsidy program is in place, while we cannot tell whether or not the average firm level production is larger with the subsidy program.[55]

The final case investigates the impact of higher adjustment costs. Here, hiring and firing costs are set equivalent to the annual wage. The results are also provided by Table (3.4). The fraction of subsidized workers rises further to 1.57%. The rate of reallocation in terms of exit and job turnover falls again with the subsidy: the exit rate drops from 5.08% to 4.84%, while the job turnover rate falls from 3.69% to 3.43%. A comparison with the "low adjustment costs" case reveals that the exit rate rises while the job turnover rate drops with the increase in adjustment costs. Note that high labor adjustment costs have two competing effects on exit behavior: while high firing costs increase the cost of exiting and therefore prevent exit, high labor adjustment costs (both hiring and firing) reduce the expected value and encourage exit. In our example, the exit rate rises with higher adjustment costs, indicating that the "encouragement" effect of high firing costs outweighs the "prevention" effect of high firing costs. However, higher adjustment costs still seem to reduce the job turnover rate. Furthermore, the impact on the average size of firms is greater with higher adjustment costs, as average employment rises by 1.87% compared to the benchmark.

Average productivity based on employment falls by 1.7%, while unlike the first two cases, average productivity based on utilized workers falls by 0.12%. The drop in the second productivity measure implies that the distortion that the subsidy generates in the reallocation measures is greater with the "higher adjustment costs," and this offsets the productivity gain generated by the flexible production adjustment provided by the subsidy. When productivity is adjusted for hiring/firing costs, the drop in productivity is not as severe, as a result of the gains accrued

[55] This is because the cdf for $e(s = 2/3)$ and the cdf for $e(s = 2/3)$ intersect (around the employment level equals to 2.3).

from smaller adjustment costs. However, productivity falls again below the baseline employment productivity, by 2.04%, when it is adjusted for both labor adjustment and subsidy costs.

Even though the direct effect of the subsidy on productivity observed in this section are small in all three cases, the indirect effect of the subsidy over the business cycle can be substantially larger. We will examine these results in the next section.

### 3.4.3 Simulation Results

In the previous section, we saw that the direct effect of the subsidy on steady-state productivity is more or less proportional to the number of subsidized workers. However, the simulation exercises reveal that even when the productivity effect is small, the effects of the subsidy on output and employment dynamics over business cycles are quite striking. Accordingly, in this section, cyclical implications of the subsidy program are highlighted via simulation.

For each simulation, a sequence of profitability shocks is generated for 150 periods from the Markov-process described above for 5000 firms. The idiosyncratic component of the profitability shock varies across firms, while the aggregate component is shared by all firms. Furthermore, each time a firm exits, a new firm enters to replace the old firm so that the total number of firms remains constant using the steady-state condition.[56] When a new firm enters, a new sequence of the idiosyncratic component of profitability shocks is drawn from the distribution, and the firm starts with zero employment.

In addition to profitability shocks, a sequence of eligibility is also generated for all firms based on the unconditional probability $\pi$. After generating employment, output, entry and exit behavior for 5000 firms for 150 periods, the first 50 periods are deleted in order to eliminate the

[56] Although exits would likely exceed entries during downturns, this simulation abstracts from the variations in net entries over the business cycle. As long as the effect of the subsidy program on the variations in net entries is small, normalization with the benchmark case insures that this simplification does not pose a significant problem in assessing the policy impact. If the reduced variation in net entries is incorporated, both employment and output should be less volatile than suggested by the results here. This implies that the employment volatility results will be enhanced, while the output volatility results will be mitigated.

effects of the initial distribution. This entire exercise, in turn, was repeated 100 times to obtain the mean and the standard deviation of each statistic. Note that given the procedure described above, 'total output' and 'total employment' in this exercise refer to the total sample of 5000 firms.

Table 3.5: Summary statistics obtained from simulation exercises with low adjustment costs: $\tau_h = 0.8$, $\tau_f = 0.8$.

| | $s = 0$ | $s = 2/3$ | Ratio |
|---|---|---|---|
| Correlations between | | | |
| — total output and average productivity (n) | 0.9870 | 0.9895 | 1.0025 |
| | (0.0007) | (0.0006) | |
| — total output and average productivity (e) | | 0.9891 | |
| | | (0.0006) | |
| Standard deviations of | | | |
| — total output | 0.1670 | 0.1717 | 1.0284 |
| | (0.0006) | (0.0006) | |
| — total employment | 0.0424 | 0.0399 | 0.9409 |
| | (0.0007) | (0.0007) | |
| — average productivity | 0.1320 | 0.1387 | 1.0512 |
| | (0.0003) | (0.0003) | |
| — job creation rate | 0.0205 | 0.0198 | 0.9680 |
| | (0.0003) | (0.0002) | |
| — job destruction rate | 0.0200 | 0.0186 | 0.9304 |
| | (0.0002) | (0.0002) | |

First we examine the "low adjustment costs" case that sets both hiring and firing costs to 80% of the annual wage. Then, we investigate the "high adjustment costs" case where both hiring and firing costs are increased to 100% of the annual wage to investigate its impact. Table (3.5) reports statistics obtained from simulating the "low adjustment costs" case. It provides statistics for $s = 0$ and $s = 2/3$, as well as their ratio, with the benchmark figure set as a denominator. Standard deviations of each statistics are reported in parentheses. Note that output, employment and productivity are now in measured in natural logarithms. As the 'ratio' column shows, the correlation between total output and average productivity rises by 0.25% with the subsidy indicating that the procyclicality of productivity is stronger with the subsidy program.

However, the predicted increase is very small.

The JIP database presented in section (3.2.2) showed that the correlation between TFP and real gross output falls from 0.7916 to 0.7843 when the subsidy adjustment is made, and the correlation between TFP and real value added falls from 0.9921 to 0.9906. In this theoretical exercise, the correlation between total output and average productivity falls slightly, from 0.9895 to 0.9891, when subsidized workers are taken into account in calculating average productivity (i.e. when I use equation (3.19) instead of (3.18)).

Perhaps the most significant finding of this exercise is that the standard deviation of output increases on average by 2.84% when $s = 2/3$ compared to when $s = 0$. This is a substantial increase in volatility given that the fraction of subsidized workers is only 1.3% of total employment at the steady-state. Intuitively, this results from a symmetric increase in output sensitivity to aggregate shocks: when the bad aggregate shock hits the economy, total output is lower than otherwise as the subsidy allows for a reduction in output while sustaining employment. When the good aggregate shock hits the economy, total output is higher with the subsidy program as firms spend less on hiring. Since the subsidy program keeps average employment higher, firms can more readily raise production in times of favorable shocks. This generates more volatility in total output.

On the contrary, the volatility of employment falls by about 6% with the subsidy program in place. This matches the objective of the government to reduce undesired fluctuation in employment due to business cycles. The reduction comes from reduced job destruction during unfavorable aggregate conditions as well as stunted job creation during favorable times. The standard deviation of job creation falls by about 3.2% with the subsidy, whereas the standard deviation of job destruction falls by about 7%. Finally, the standard deviation of average productivity rises by 5.12%.[57]

[57] Since labor productivity is now expressed in logs (i.e. $\ln(Y/N)$), the following formula applies:

$$var(\ln(Y/N)) = var(\ln Y) + var(\ln N) - 2cov(\ln Y, \ln N). \tag{3.20}$$

Note that since the variance of output is much larger than the variance of employment, the increase in the variance of output results in the higher variance of productivity, even with the reduction in the variance of employment.

Table 3.6: Summary statistics obtained from simulation exercises with high adjustment costs: $\tau_h = 1$, $\tau_f = 1$.

| | $s = 0$ | $s = 2/3$ | Ratio |
|---|---|---|---|
| Correlations between | | | |
| — total output and average productivity (n) | 0.9896 | 0.9927 | 1.0032 |
| | (0.0007) | (0.0007) | |
| — total output and average productivity (e) | | 0.9921 | |
| | | (0.0007) | |
| Standard deviations of | | | |
| — total output | 0.1630 | 0.1687 | 1.0348 |
| | (0.0007) | (0.0007) | |
| — total employment | 0.0373 | 0.0327 | 0.8759 |
| | (0.0008) | (0.0009) | |
| — average productivity | 0.1322 | 0.1418 | 1.0722 |
| | (0.0003) | (0.0004) | |
| — job creation rate | 0.0177 | 0.0159 | 0.9008 |
| | (0.0002) | (0.0003) | |
| — job destruction rate | 0.0182 | 0.0149 | 0.8225 |
| | (0.0002) | (0.0002) | |

Table (3.6) highlights the results of the "high adjustment costs" case. The fraction of subsidized workers given by the stationary distribution in this case is 1.59%. The results for correlations are similar to the "low adjustment costs" case except that the correlations are slightly higher due to higher adjustment costs. The volatility of output increases by about 3.5%, but the volatility of employment falls substantially by about 12%. This result is generated by a reduction in the volatility of job creation by 10% and job destruction by 18%. In addition, the standard deviation of average productivity rises by 7.2%.

The comparison between the "high adjustment costs" and "low adjustment costs" cases reveals that even when the effect of the subsidy on the steady-state employment and job reallocation rate is trivial, the effect on the volatility of employment over the business cycle is substantial. This result is mainly driven by the reduced sensitivity of job creation and destruction to aggregate

Furthermore, the covariance between output and employment falls with the subsidy as expected, thereby further increasing the variance of productivity under the subsidy case relative to the benchmark case.

shocks. Hence, the policy leads to a substantial reduction in the volatility of job churning over the business cycles. Finally, although it is not reported in this paper, the volatility of output increases by 4.2% and the volatility of employment falls by 10% when the size of adjustment costs are further increased to $\tau_h = \tau_f = 1.5$, for the fraction of subsidized workers equal to 2%.[58]

## 3.5 Conclusion

This chapter examined the effects of the EAS, Japan's major employment insurance program, on average productivity, employment, and the volatility of output and employment over the business cycle, through the examination of the Iron and Steel industry. The partial equilibrium model described in this chapter shows that the subsidy reduces average productivity primarily by increasing the number of unutilized workers, although the direct impact of the subsidy on productivity is predicted to be small, given that the fraction of subsidized workers is small. However, simulation exercises reveal that the subsidy may have a substantial impact on the volatility of output and employment. In particular, when hiring and firing costs are set equal to 80% of the annual wage, output volatility increases by 2.8% over the business cycles with the subsidy, while employment volatility drops by 6%, even when the fraction of subsidized workers is about 1.3%. When hiring and firing costs are increased equivalent to the annual wage, the volatility of employment drops by 12% while the volatility of output increases by 3.5%.

While measures such as productivity, employment and output volatility are often used to evaluate welfare, I do not intend to draw a normative conclusion on the welfare effect of the subsidy program. However, I believe that the implications highlighted in this theoretical exercise are important ones, providing policymakers a better understanding of the program, thereby allowing them to more successfully target their policy objectives. Here, I raise a couple of issues for a more complete welfare assessment. First, the paper predicts that the subsidy increases output volatility while reducing employment volatility. Hence, an assessment of the policy requires an analysis of

[58]Note that higher adjustment costs do not always enhance the effectiveness of the subsidy in reducing employment volatility as we see in the case where $\tau_h = \tau_f = 1.5$. This is because high adjustment costs of this magnitude are already associated with very low employment volatility. This reduces the effect of the subsidy.

the cost of output volatility and the benefits of employment stability.[59] Second, although some labor market imperfections are assumed for subsidy take-up to take place (i.e. firing restrictions and rigid wage), I have not investigated how the subsidy program may enhance or reduce labor market imperfections.[60] Neither have I conducted a hypothetical comparison with a benchmark without labor market imperfections.

The analysis presented here raises several additional issues for further investigation. First, since the quantitative impact of the subsidy on the volatility of output and employment is sensitive to the magnitude of labor adjustment costs, it will be important to quantify these costs accurately to evaluate the potential impact of the subsidy program. Second, the analysis treated the Iron and Steel industry as an independent economy with no interaction with other industries. New policy implications may arise if inter-industry interactions between high productivity sectors and low productivity sectors are present in the model.[61] Third, it seems worthwhile to investigate why the subsidy was so highly concentrated in the Iron and Steel sector. Finally, employment volatility during the severe recession of the 1990s was surprisingly mild in Japan compared to other industrial nations, despite the fact that EAS coverage was highly concentrated in certain sectors of the economy.[62] It would be interesting to empirically investigate what factors contributed to the stabilization of employment.

[59]For example, the subsidy program could bring a substantial benefit by promoting long-term employment if the skill/productivity of workers increases with tenure.

[60]For example, the subsidy could potentially enhance the downward rigidity of wage. Similarly, it may create less incentive to legislate reductions to firing restrictions and promote labor mobility.

[61]The subsidy program may have an inter-industry reallocation effect as some industries are more heavily subsidized than others. This feature could potentially add another dimension to the analysis of overall productivity dynamics.

[62]According to *Labor Force Survey*, the unemployment rate during the 1990s followed a steady increase rather than being cyclical. The unemployment rate at the trough from 1998-1999 was still below 5%.

# Appendix A

## Construction of Variables using the Nikkei Financial Dataset

'Total sales revenue' (var90) is used as a measure of gross output. Nominal value of sales in turn are deflated into a constant year 2000 value, using the annual averages of monthly corporate good price indices (CGPI) provided at the Bank of Japan's website in Japanese.[1] Note that CGPI is available only for the manufacturing sector at the two-digit industry level. Also, since CGPI for 'rubber' (Nikkei industry code # 13) was not available, it was omitted from the analysis. Moreover, CGPI for 'nonferrous metals' are used for 'nonferrous metals and metal products' (Nikkei industry code #19).

'Number of employed workers' (var158) is used as the measure of labor input in the productivity decomposition analysis. Note that the same series were used for the job reallocation exercises. 'Total material cost' (var292) is used as a measure of material input. Nominal value is converted into a real value using CGPI. The material cost share was calculated by dividing var292 by the 'total cost' (var306) and the labor cost share was calculated by dividing the 'total labor cost' (var293) by the 'total cost' (var306).

The measure of capital stock is constructed using the 'total tangible assets' (var21) of the Nikkei dataset. Var21 is the sum of buildings (var23), machineries (var24), transportation equipment (var25), other equipment (var26), land (var27) and others (var28). According to var260 which explains the method of depreciation of tangible assets, 84% of all observations use a constant rate of depreciation, 14% use a combination of the constant rate and the constant value, and the rest use a combination of constant rate, constant value, and the rate of depreciation proportional to output. These figures in turn are converted to a constant 1995 value using the annual average of the monthly wholesale price index (WPI) provided by the Bank of Japan for machinery and equipment. The WPI is available at the Bank of Japan's website.

[1] http://www.boj.or.jp/stat/dlong_f.htm.

## Appendix B

## Examination of the Impact of Higher Volatility of Shocks on Subsidy Applications

In this section, I discuss the implications of higher volatility of (industry level) aggregate shock processes on subsidy application decisions using the theoretical framework developed in Chapter 3. In particular, a numerical experiment is conducted to examine the impact of higher volatility on subsidy application decisions. The same framework used previously applies, except that the frequency is changed from annual to monthly in order to be consistent with the empirical analysis given in Chapter 2. Table ($B$.1) gives the parameter values for this particular experiment.

Table B.1: Parameter values used to obtain stationary distributions with monthly frequency.

| | |
|---|---|
| $w = 1$ | wage |
| $\tau_h = 3$ | hiring costs |
| $\tau_f = 3$ | firing costs |
| $c_f = 2$ | fixed cost of operation |
| $r = 0.0033$ | interest rate |
| $\beta = (1/(1+r)) = 0.9967$ | discount rate |
| $\gamma = 0.8$ | fraction of wage paid to unutilized workers |
| $\pi = 0.7$ | prob. of being eligible for the subsidy |
| $s = 2/3$ | subsidy coverage |
| $\theta = 0.55$ | labor share of total cost |
| $\rho = 0.85$ | persistence of idiosyncratic shocks |
| $\sigma_v = 0.3$ | standard deviation of $v_t$ |
| $\delta = 0.6$ | aggregate state transition probability |

To examine the impact of higher volatility, the distance between $\alpha_g$ and $\alpha_b$ is gradually increased by the increments of 0.05 while the mean is held constant. More specifically, I first set both $\alpha_g$ and $\alpha_b$ equal to 2.7, then I increased (decreased) the size of the good (bad) state by 0.025 each time, until the good shock reaches 3.3 and the bad shock reaches 2.1 at which the lowest idiosyncratic shock becomes closest to the boundary of zero.[1] Note that the symmetric aggre-

[1] As before, the lowest boundary is set at the three standard deviations of idiosyncratic shocks away from the

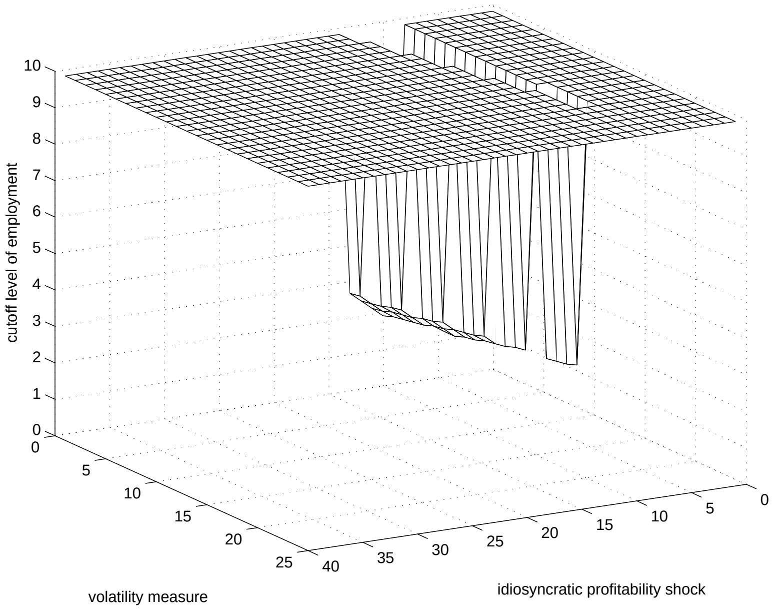


Figure B.1: Subsidy application decision rules with volatility for the good aggregate state. The higher number of volatility measures indicates higher volatility and the higher number of idiosyncratic shocks represents more favorable conditions.

gate transition probabilities preserves the mean while the distance between $\alpha_g$ and $\alpha_b$ increases. Therefore, it allows us to focus on the impact of increased aggregate volatility. Employment was discretized in 201 grid points ranging from zero to ten. Again, the upper bound was set to guarantee that the highest optimal employment does not bind.

Figure $(B.1)$ shows the subsidy application decision rules for the good aggregate state. The decision rule shows the cutoff level of employment above which subsidy applications take place, for a given level of volatility measure and idiosyncratic profitability shock. Here, volatility goes up as the measure increases from 1 to 25, and the idiosyncratic profitability shock improves as the measure increases from 1 to 40. When there are no firms applying at any given combination of idiosyncratic shock and the volatility measure, the cutoff level of employment is at its maximum level which here is set equal to 10. In general, the lower measure of idiosyncratic shocks should be associated with an increased chance of subsidy applications, as expanding firms do not apply. At the very low level of idiosyncratic shocks, however, firms decide to exit from the market and therefore, they do not apply for the subsidy. In the good aggregate state, subsidy applications

mean.

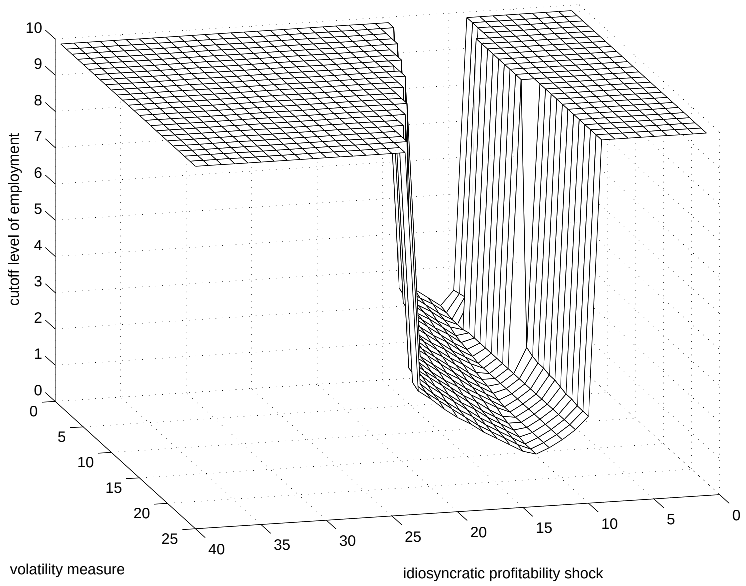


Figure B.2: Subsidy application decision rules with volatility for the bad aggregate state. The higher number of volatility measures indicates higher volatility and the higher number of idiosyncratic shocks represents more favorable conditions.

fall as the volatility measure increases, since the mean profitability shock captured by $\alpha_g$ increases with a rise in volatility

On the other hand, the subsidy applications increase as the volatility measure goes up in the bad aggregate state, and this rise is larger than the reduction in subsidy applications in the good aggregate state. Therefore, overall subsidy applications increase with volatility. Figure ($B$.2) shows the subsidy application decision rules for the bad aggregate state. Here we can see that the area for subsidy applications continues to expand as the degree of volatility increases.

Finally, a stationary distribution with low volatility was compared with a stationary distribution with high volatility in Table ($B$.2). Here, the benchmark case is the low volatility case. Moreover, I use an asymmetric probability matrix this time in which the probability of a good state continuing is 0.7 and the probability of bad state continuing is 0.3, as the equilibrium level of subsidized workers turned out to be too large with the previous symmetric transition probability and the other parameters given by table ($B$.1). The low volatility case sets $\alpha_g = 2.8$ and $\alpha_b = 2.45$ while the high volatility case sets $\alpha_g = 2.94$ and $\alpha_b = 2.12$. The unconditional expected mean for both is approximately 2.695.

Table B.2: Summary statistics of stationary distributions with low and high aggregate volatility.

| | Low Volatility | High Volatility |
|---|---|---|
| | $\alpha_g = 2.80$ | $\alpha_g = 2.94$ |
| | $\alpha_b = 2.45$ | $\alpha_b = 2.12$ |
| Fraction of workers covered by the subsidy | 0.0074 | 0.0226 |
| Exit rate | 0.0174 | 0.0160 |
| Job turnover rate | 0.0181 | 0.0167 |
| | | |
| Total number of firms | 1.0000 | 0.9999 |
| Average firm level employment | 1.0000 | 1.0049 |
| Average firm level output | 1.0000 | 0.9937 |
| | | |
| Average productivity based on employment | 1.0000 | 0.9888 |
| — adjusted for hiring and firing costs | 1.0000 | 0.9927 |
| — adjusted for hiring, firing and subsidy costs | 1.0000 | 0.9868 |
| Average productivity based on utilized workers | 1.0000 | 1.0045 |

The table shows that the steady-state fraction of subsidized workers with low volatility is 0.74%, and it increases to 2.26% with high volatility. The exit rate falls with volatility from 1.74% to 1.6%, as more firms with low profitability shock decide to stay in the market by taking advantage of the subsidy. Similarly, the job turnover rate falls from 1.81% to 1.67% since the subsidy reduces both job creation and job destruction at the steady-state. Other results are based on the same intuitions we've seen in the previous sections.

# Appendix C

## Industry Correspondence used for the Construction of the Demand Instrument

Table ($C$.1) shows the concordance of the industry classifications for the manufacturing sector for the following three data sources: the JIP database, *Indices of Industrial Production* published by the Japanese Ministry of Economy, Trade and Industry (METI), and *Corporate Good Price Indices* (CGPI) constructed by the Bank of Japan.

This matching was employed for the construction of a demand instrument, which was constructed to investigate the output responses to demand shocks in the Iron and Steel industry. I used the input-output table of the JIP database to create the annual weight which captures the annual share of consumption of the Iron and Steel industry's shipments among downstream industries. Then the original monthly series of shipment index of the downstream industries, taken from the *Indices of Industrial Production*, were deflated by CGPI, and the real growth rate was calculated by taking the log difference. Finally, the weighted average growth rate of the downstream industries was calculated by using the weights described above.

Although the classification with smaller industrial units is available for *Indices of Industrial Production*, it does not easily correspond with the classifications from the JIP database. Furthermore, CGPI is not available for smaller industrial units. Therefore, the JIP industries were aggregated to match with a broader classification of the *Indices of Industrial Production*.

Table C.1: Concordance of industry classifications between JIP dataset, *Indices of Industrial Production* (METI), and CGPI.

| JIP code | JIP industry name | METI (last 3-digit) | CGPI |
|---|---|---|---|
| 7 | Coal, lignite mining | 132 | Minerals |
| 8 | Metal mining | | |
| 9 | Crude oil, natural gas exploration | | |
| 10 | Quarry, gravel extraction, other mining | | |
| 11 | Livestock products | 110 | Processed foodstuffs |
| 12 | Processed marine products | | |
| 13 | Rice polishing, flour milling | | |
| 14 | Other foods | | |
| 15 | Beverages | | |
| 16 | Tobacco | | |
| 17 | Silk | 103 | Textile products |
| 18 | Spinning | | |
| 19 | Fabrics and other textile products | | |
| 20 | Apparel and accessories | | |
| 21 | Lumber and wood products | 127 | Lumber and wood products |
| 22 | Furniture | 124 | Other manufacturing |
| 23 | Pulp, paper, paper products | 98 | Pulp, paper and related products |
| 24 | Publishing and printing | | |
| 25 | Leather and leather products | 123 | Other manufacturing |
| 26 | Rubber products | 122 | Other manufacturing |
| 27 | Basic chemicals | 77 | Chemicals and related products |
| 28 | Chemical fibers | | |
| 29 | Other chemicals | | |
| 30 | Petroleum products | 94 | Petroleum and coal products |
| 31 | Coal products | | |
| 32 | Stone, clay and glass products | 72 | Ceramic, stone and clay products |
| 33 | Steel manufacturing | 3 | Iron and steel |
| 34 | Other steel | | |
| 35 | Non-ferrous metals | 11 | Nonferrous metals |
| 36 | Metal products | 16 | Metal products |
| 37 | General machinery equipment | 21 | General machinery and equipment |
| 38 | Electrical machinery | 405 | Electrical machinery and equipment |
| 39 | Equipment and supplies for household use | | |
| 40 | Other electrical machinery | | |
| 41 | Motor vehicles | 57 | Transportation equipment |
| 42 | Ships | | |
| 43 | Other transportation equipment | | |
| 44 | Precision machinery and equipment | 68 | Precision instruments |
| 45 | Other manufacturing | 128 | Other manufacturing |

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