Analysis of Changes in Japan's Unemployment Rate Using Gross Flow Data

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Using the flow data between the three states of employment, unemployment and not-in-the-labor-force, I undertook a detailed examination of factors contributing to changes in Japan's unemployment rate.

The results of the analysis provide the following explanations for Japan's rising unemployment rate since 1991. First, the transition probability from employment to unemployment has risen, and at the same time the transition rate from unemployment to employment has declined significantly. Second, the transition probability from unemployment to not-in-the-labor-force has declined for both men and women, resulting in the accumulation of unemployment. Third, the results point to the possibility that the unemployment rate was also pushed up by the flow of workers from not-in-the-labor force to unemployment. Parallel to a decline in the transition probability from not-in-the-labor-force to employment, an increased inflow of men from not-in-the-labor-force to unemployment began in the mid-1990s. The same trend is observable for women beginning between the end of the 1990s and 2000.

Next, I estimated the Phillips curve using the flow data as a source of additional information for forecasting price trends. The results indicate that the forecasting performance of the Phillips curve can in fact be improved by using flow data between employment and unemployment that are sensitive to trends in price levels and business conditions.

Keywords: Unemployment rate; Flow data analysis; Discouraged worker effect; Added worker effect; Price-level projections using Phillips curve
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I. Introduction

Japan's unemployment rate has gradually risen since 1991. According to the latest available statistics, Japan's unemployment rate rose to 5.5 percent in December 2001, the highest level since statistics have been compiled. Some argue that Japan may face far greater unemployment if the disposal of nonperforming loans is accelerated and if fundamental industrial structural reform leads to an increase in corporate bankruptcies.[1] The general view widely shared by researchers by the mid-1990s was that Japan's unemployment rate, in comparison to that of other industrialized countries, was subject to less fluctuation and did not increase substantially during recessions. It may well be that there is now ample room to reexamine these views.

As represented by Beveridge curve analysis, most of the earlier research analyzing Japan's unemployment focused on changes in the level of unemployment rate. This may have been a feasible approach when entry into and exit from the labor market was limited to time of school graduation and time of retirement, such that flows between the labor force (employment plus unemployment) and not-in-the-labor-force was stable over time, such that most unemployed persons were job losers.

However, it now appears that the rise in Japan's unemployment rate cannot be sufficiently explained by the increase in the number of workers losing their jobs. For instance, the unemployed can be broken down into the following four categories by reason: (1) quit job involuntarily, (2) quit job voluntarily, (3) left school, and (4) other. Of the total 3.4 million unemployed in 2001, 850,000 fell under the category of "other" (*Labour Force Survey* [Statistics Bureau and Statistics Center]).[2,3] Regarding this categorization, it is possible to interpret "other" as consisting of those who previously were not in the labor force and who are now entering the labor force. Continued structural reform and corporate restructuring can be expected to further increase the number of unemployed. Under such conditions, housewives—previously classified as not-in-the-labor-force—may start looking for jobs to maintain household income levels following the loss of the husband's job (the "added worker effect"). That is, a rapid increase in the unemployment rate may further increase the unemployment rate by increasing the number of "other" at the same time.

In evaluating the changes in the unemployment rate, a closer look at the outflow from the unemployment pool is also necessary. If labor market conditions deteriorate further, people unable to find jobs may give up their search and leave the labor force

1. Various estimates have been made of the magnitude of unemployment that would be generated in the process of the disposal of nonperforming loans, such as 1.5 million (Japan Research Institute [2001]) and 1.3 million (NLI Research Institute [2001]). The Cabinet Office (2001) has estimated that 390,000–600,000 people would initially lose their jobs, but that 180,000–270,000 would find new employment while 90,000–150,000 would exit the labor force, thus yielding an additional unemployment of about 130,000–190,000.
2. The *Labour Force Survey* is conducted in the last week of each month and defines "unemployed" as a person who (1) has no job and did not work at all during the reference week, (2) is ready to work if work is available, and (3) is engaged in any job-seeking activity or was preparing to start business during the reference week (including those awaiting the outcome of the job-seeking activity done in the past). This definition of unemployment conforms with international standards established by the International Labour Organisation (ILO).
3. From January 2002, the reason for seeking a job had been changed into six categories: "mandatory retirement," "reasons due to employer," "quit job voluntarily," "left school," "need to earn income," and "other."

(the "discouraged worker effect"). This could result in improved unemployment rates (even if other conditions remain unchanged). Any such decline in unemployment rates obviously differs from a decline resulting from economic recovery. In other words, it is likely that not all changes in the unemployment rate arise from the same underlying labor market conditions. This means that policymakers could obtain misleading information based only on observed changes in the level of unemployment. Thus, a closer look at the flows into and out of unemployment that lie beneath changes in total unemployment may be necessary for policymakers. In this regard, this paper examines the rapid rise in Japan's unemployment rate during the 1990s by using flow data.

To the best of my knowledge, there is relatively little prior research, both in Japan and other countries, using macro flow data from a business cycle or macroeconomic perspective.[4] The best known among the limited instances of earlier research is Blanchard and Diamond (1990), who examined the changes in the flow of workers caused by a cyclical shock. The authors pointed out that the U.S. unemployment rate is affected by the mutual interaction of movements unique to each demographic property. Recent U.S. research includes Bleakley *et al.* (1999).[5] Their study showed that more detailed information on labor market conditions, obtained by using the time series that they developed for flows into and out of unemployment by reason (job losers, job leavers, etc.), improves forecasts of inflation relative to standard Phillips curve models.

For Japan, a series of papers by Mizuno (1982, 1983, 1992) is the only time-series analysis using macro flow data. Mizuno undertook a detailed examination to determine how the added worker effect, discouraged worker effect, and delayed entry effect have affected the rise in unemployment and the decline in the participation ratio during recessions in the 1970s and 1980s.[6]

The remainder of the paper is organized as follows. Section II presents a brief description of the flow data used in this paper. Section III takes a closer look between the flows into and out of the three states and the business cycles. Section IV shows that more detailed information on labor market conditions obtained from the flow data does improve forecasts of inflation, relative to the standard Phillips curve model using unemployment rate as an explanatory variable. The last section summarizes the results of this paper.

4. After the 1970s, extensive efforts were made to analyze the inter-state transition of workers from a more micro perspective using micro data, and in particular to verify the existence of the added worker effect and the discouraged worker effect. The best known in these areas are studies done by Heckman and Macurdy (1980, 1982). See also Maloney (1991), Spletzer (1997), Gruber and Cullen (1996), and Stephens (2001). For the prior Japanese research using micro data, see Higuchi (1989), Higuchi and Abe (1999), and Abe and Ohta (2001).
5. For prior research using the flow data of European countries, see Burda and Wyplosz (1994), for example.
6. Ono (1982, 1989) showed that the ratio of hidden unemployment in not-in-the-labor-force increases during recessions, and therefore that the discouraged worker effect existed in Japan. To verify this effect, Mizuno (1982, 1983, 1992) proposed the use of flow data to observe the actual movement of workers during recessions. Mizuno concluded that the magnitude of hidden unemployment in not-in-the-labor-force increased not so much because of the discouraged worker effect, but more because of the "delayed entry into labor force effect" (i.e., the number of people choosing to remain in the not-in-the-labor-force increases during recessions).

II. Data Description

The flow data used in this paper are based on the monthly *Labour Force Survey* of the Statistics Bureau and Statistics Center. In the *Labour Force Survey*, 50 percent of the sample is surveyed over two consecutive months. By matching workers across the two months, it becomes possible to observe how workers in E (employed), U (unemployed), or N (not-in-the-labor-force) in the previous month have moved to other states in the following month.

The movement of workers observed over two consecutive months is categorized into the nine categories of flow shown in Table 1. Two consecutive months of employment is indicated as (EE); a worker moving from employment in the former month to unemployment in the latter month is (EU); movement from employment to not-in-the-labor-force is (EN); movement from unemployment to employment is (UE); two consecutive months of unemployment is (UU); movement from unemployment to not-in-the-labor-force is (UN); movement from not-in-the-labor-force to employment is (NE); a person previously not-in-the-labor-force who has started to look for work and is unemployed is (NU); and, two consecutive months of not-in-the-labor-force is (NN).

Table 1 Types of Flows

Status in previous month (t – 1)	Status in current month (t)		
	E_t	U_t	N_t
E_{t-1}	EE	EU	EN
U_{t-1}	UE	UU	UN
N_{t-1}	NE	NU	NN

Flow data can provide valuable information concerning labor market conditions. However, due caution must be exercised in the use of flow data, as they are known to contain various forms of bias.[7] Because of these biases, in certain instances, the simple addition of flow data does not necessarily yield figures that are consistent with the stock data. Therefore, it has been pointed out that "the flow data may not faithfully reflect actual labor market conditions" (Ono [1982, 1989]). To eliminate these problems as much as possible, the former Ministry of Labour made adjustments to the gross flow data that are more consistent with the movement of the stock data. The data used in this paper are this adjusted series, being published in the *White Paper on Labour* at several year intervals (the 1985, 1987, 1989, 1990 1991, 1992, 1993, 1994, 1998, 1999, and 2000 editions), which I have linked together. The flow data published in the *White Paper* consist of 12-month cumulative flows (12-month sum of

7. The major biases often mentioned in the flow data research are (1) sample bias, (2) misclassification errors, and (3) rotation group bias. See Abowd and Zellner (1985) and Poterba and Summers (1986) for the details of these errors. Although these errors may be contained in the flow data at a given point in time, Barkume and Horvath (1995) pointed out that if these biases could be assumed to remain constant over time, useful information could still be obtained by observing the time-series movement of the flow data.

monthly flow data), which have been converted into quarterly data. The 12-month cumulative flow is advantageous since it eliminates systematic seasonal fluctuations.[8]

Other than problems mentioned above, the flow data have the following limitations.

First, the flow data used in this paper cannot classify worker flows by reason of movement. Therefore, exit from the labor force because of mandatory retirement cannot be distinguished from the exit caused by discouragement in seeking jobs. Also, the permanent entry into the labor force by women undergoing a change in their attitude toward work cannot be distinguished from women entering the labor force in response to declining household income due to the reduced earnings of their husbands. To cope with this issue, I have limited the sample period of this analysis to the relatively short period between the mid-1980s and 2000, and have assumed that population structure and preferences related to labor supply have remained constant during this period.

Second, consecutive data for any individual are available for no more than two months. Hence, for example, *NU* flow may either be a long-term unemployed person who by coincidence stopped looking for work in the month surveyed but again started to look for work in the following month, or a person not in the labor force for an extended period who by coincidence started looking for work in the month surveyed.

Third, the adequacy of the *U* and *N* classifications has been debated for nearly 20 years, leading to very active discussions of the need to subdivide not-in-the-labor-force (*N*) into persons who want jobs but are not actively searching (referred to as "*M*: marginally attached," indicating relative closeness to the labor market), and persons with no interest in taking up jobs (referred to as "*O*: others").[9,10] In the case of Japan, information on *M* is limited to once-a-year data from the *Report on the Special Survey of the Labour Force Survey* (twice a year since 1992).[11] As our main interest in this paper is to examine the flow data from the perspective of the business cycle, I have restricted myself to flows in and out of the three states of *E*, *U*, and *N* for which monthly flow data are available.

8. See Ministry of Labour (1985) for details of the adjustment method. It should be noted, however, that this series has the possibility of generating a new bias, which occurs when taking the simple average of 12-month cumulative data to convert into quarterly data. Nevertheless, I used these data, since this adjusted series was the only available consecutive data at the time of this analysis.
9. For example, Clark and Summers (1979) pointed out that the borderline between *U* and *N* was unclear, and that the classifications used in the existing statistics failed to accurately reflect the real dynamics of the labor market. As opposed to this, Flinn and Heckman (1983) suggested that *U* and *N* should be treated as clearly different states, since the probability of finding a job is higher for *U* than *N*. See also Gönül (1992) and Tano (1993).
10. Research using *M* as a fourth state is led by Canada. Using Canadian data, Jones and Riddell (1999) analyzed the four-state-flows (*E*, *U*, *M*, *O*) and concluded that the three-state *E*, *U*, and *N* classification fails to accurately capture the dynamics of the labor market. See also Jones and Riddell (1998) and Castillo (1998).
11. In the revision of January 2002, Japan's *Labour Force Survey* and the *Report on the Special Survey of the Labour Force Survey* were integrated. Due to this revision, detailed information on unemployment and not-in-the-labor-force will be available on a monthly basis. In addition, since the samples of the two surveys have been merged, with the accumulation of data over time, it should be possible to undertake the same type of detailed flow data analysis as conducted in Canada mentioned in Footnote 10.

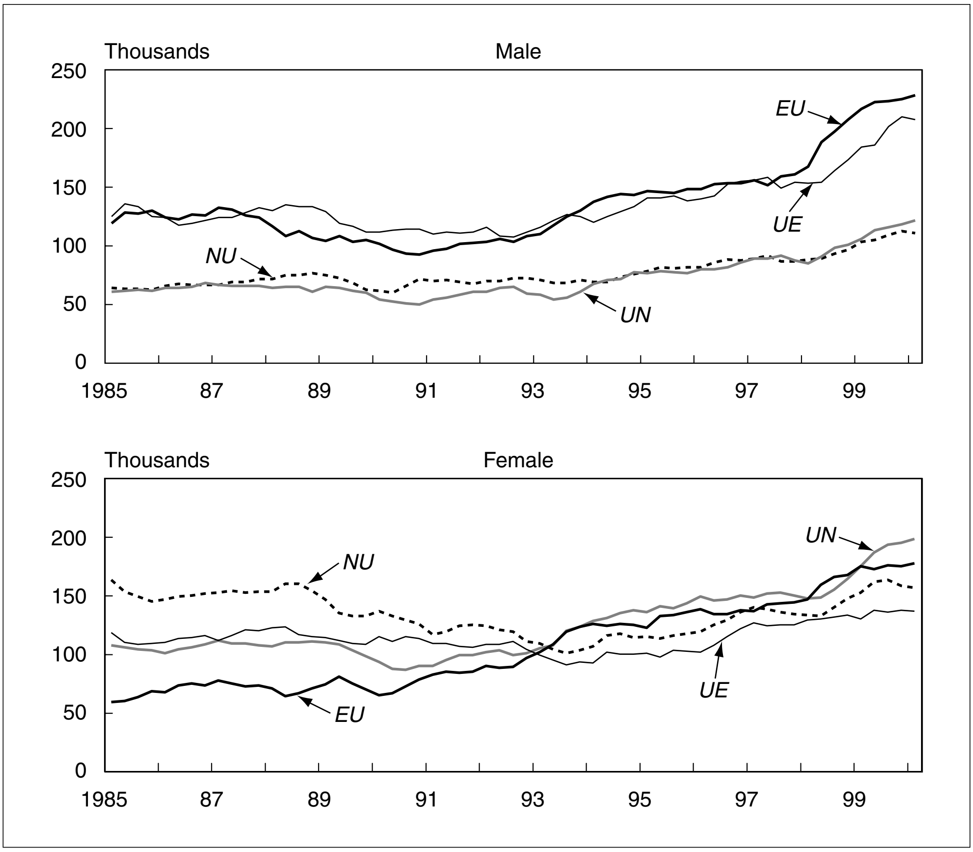
III. Analysis Using Flow Data: Part 1

A. Analysis of the Determinants of Changes in Unemployment Rate Using Flow Data

Figure 1 gives four different series of the flows for the last 15 years. In Figure 1, we can see that *EU* and *NU* flows have increased steadily since the bubble burst, for both men and women. At the same time, the outflows from the unemployment pool, both *UE* and *UN* flows, also show a sharp rise since 1993. The figure tells us that Japanese labor markets in the 1990s experienced a large flux of both inflows and outflows. What was the cause of these large increases in labor flows? The transition probabilities may provide some clue to this matter.

Transition probability is derived by dividing the flow for each period by the stock of the previous period.[12] That is, the transition probability *ue* (= UE/U_{-1}) indicates how many percent of persons unemployed in period 1 will be employed in the next period (the lowercase flows appearing hereafter in the text and figures of this paper

Figure 1 Trends in Male and Female Flows



12. The quarterly averages of 12-month cumulative flows are equivalent to a 14-month backward-weighted moving average of monthly flows. Likewise, 14-month backward-weighted moving averages have been used in the denominator for the computation of transition probabilities.

represent transition probabilities). Thus, it can be considered that the *UE* flow can be decomposed into the transition probability *ue* and the stock *U*.

Figure 2 shows that the increases in *eu* and *nu* probabilities are the dominant factors of increase in *EU* and *NU* flows in the 1990s.[13] On the other hand, *UE* and *UN* flows show different pictures (Figure 3). While the increase in unemployment (*U*) contributes to the increase in *UE* and *UN* flows, the decrease in transition probabilities of *ue* and *un* applies downward pressure on these flows. In other words, even though *UE* and *UN* flows seem to be increasing as a result of the large volume of inflows, a growing number of unemployed are accumulating in the unemployment pool due to the decreasing probabilities of *ue* and *un*.

To observe this in greater detail, let us take a look at the transition probabilities (shown in percent) of each flow (Figure 4).

The transition probability from employment into the unemployment pool (*eu* in the top graph of Figure 4) bottomed out around 1991. After that, *eu* for both men and women began to rise and this trend sharply accelerated after 1997.

The transition probability from not-in-the-labor-force into the unemployment pool (*nu*) of men continued to decline until the second quarter of 1990 and thereafter remained flat for a few years. Then it began to rise in the second quarter of 1993. The *nu* for men after 1999 is particularly noteworthy, as it reached levels never before experienced. In the case of women, *nu* followed a secular downward trend until the third quarter of 1993 and thereafter began to rise.

Next, the transition probability from the unemployment pool to employment (*ue* in the middle graph of Figure 4) rose for both men and women during the bubble period around 1990. Thereafter, *ue* began to decline after 1992. The decline was particularly sharp for women. After peaking at around 20 percent, *ue* for women had been halved by the first quarter of 2000 when it stood near 10 percent.

As for the transition from the unemployment pool to not-in-the-labor-force (*un*), a gradual decline is observed for both men and women from 1993. The secular decline in *ue* and *un* beginning around 1993 indicates that the ratio of people remaining in the unemployment pool has been increasing at the same time (*uu*: persons remaining unemployed during two consecutive months).

Turning next to the direct transition of workers from not-in-the-labor-force to employment with no intermediate stop in the unemployment pool (the bottom graph in Figure 4), *ne* rose rapidly for both men and women in the second half of the 1980s.[14] However, by the second half of the 1990s, the level of *ne* itself had fallen substantially. This trend was particularly visible for women.

Regarding the transition from employment to not-in-the-labor-force (*en*), a major difference is observed between men and women. In the case of men, *en* has risen slightly during the second half of the 1990s. In contrast, the level of *en* for women

13. The decomposition taken in Figures 2 and 3 is calculated as follows. For example, the *UE* flow can be expressed as $UE = ue \times U$. The change in *UE* flow between time 1 and time 2 ($\Delta UE = UE_2 - UE_1$) can be decomposed and written as $\Delta UE = ue_1(U_2 - U_1) + U_2(ue_2 - ue_1)$. This equation shows that changes in the *UE* flow can be explained by changes in the number of unemployed (first term on the right-hand side) and changes in unemployment-to-employment transition probability (second term).

14. Data for flows of *en* and *ne* were unavailable for certain periods, so that the data series is interrupted. In this paper, I have indicated the flows for five-year periods in both the latter half of the 1980s and 1990s.

Figure 2 Contributions of Changes in Transition Probability and Employment, Unemployment, and Not-in-the-Labor-Force to Changes in Flows (1)

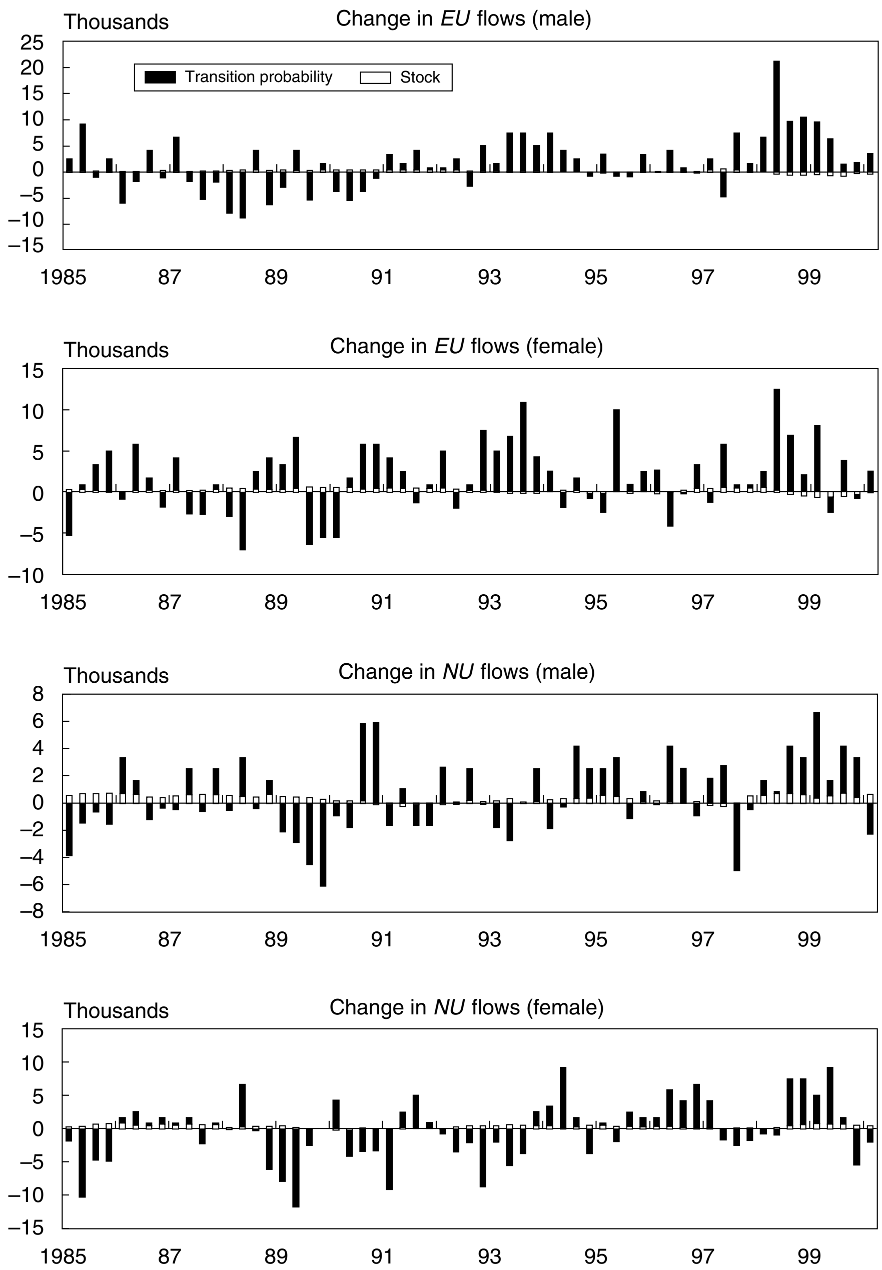


Figure 3 Contributions of Changes in Transition Probability and Employment, Unemployment, and Not-in-the-Labor-Force to Changes in Flows (2)

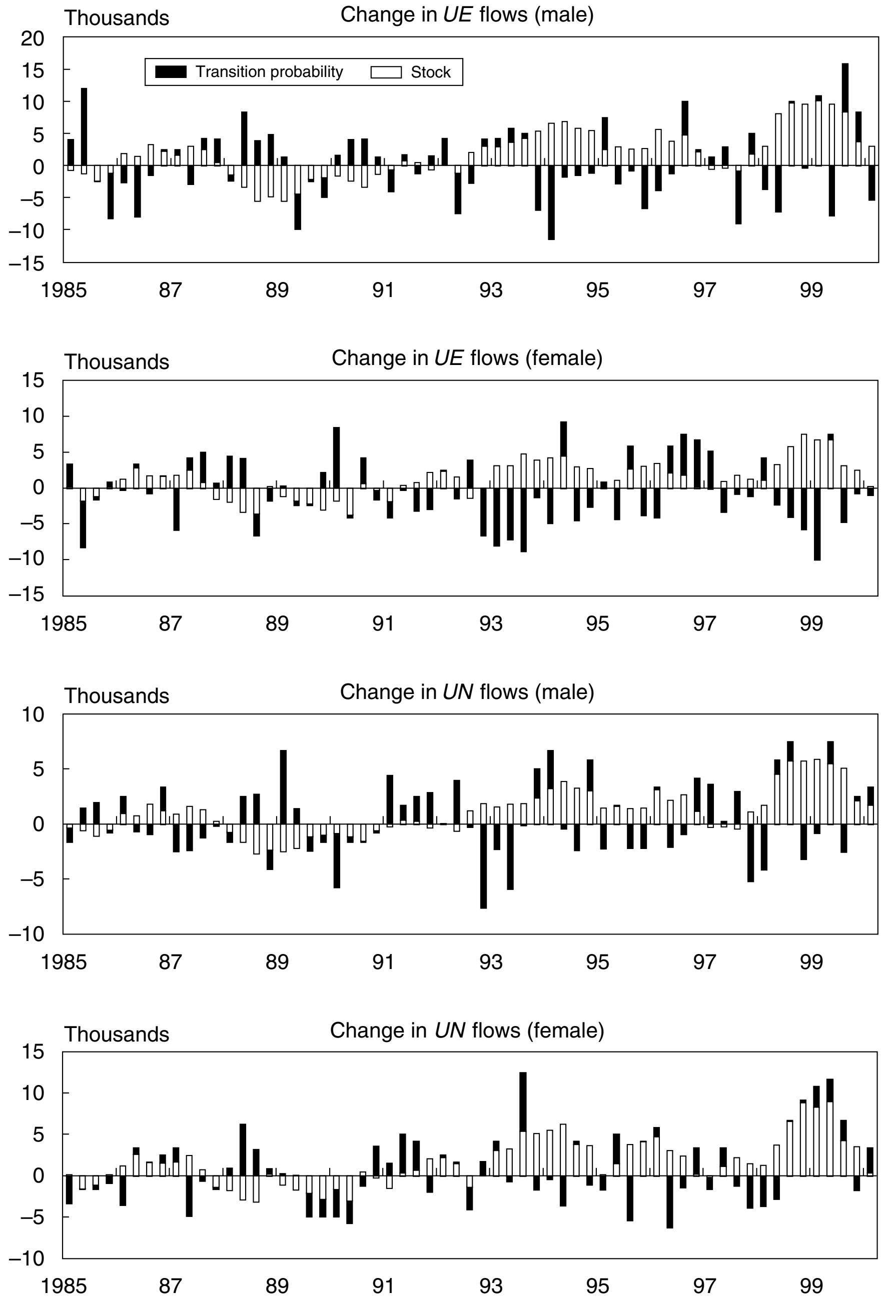
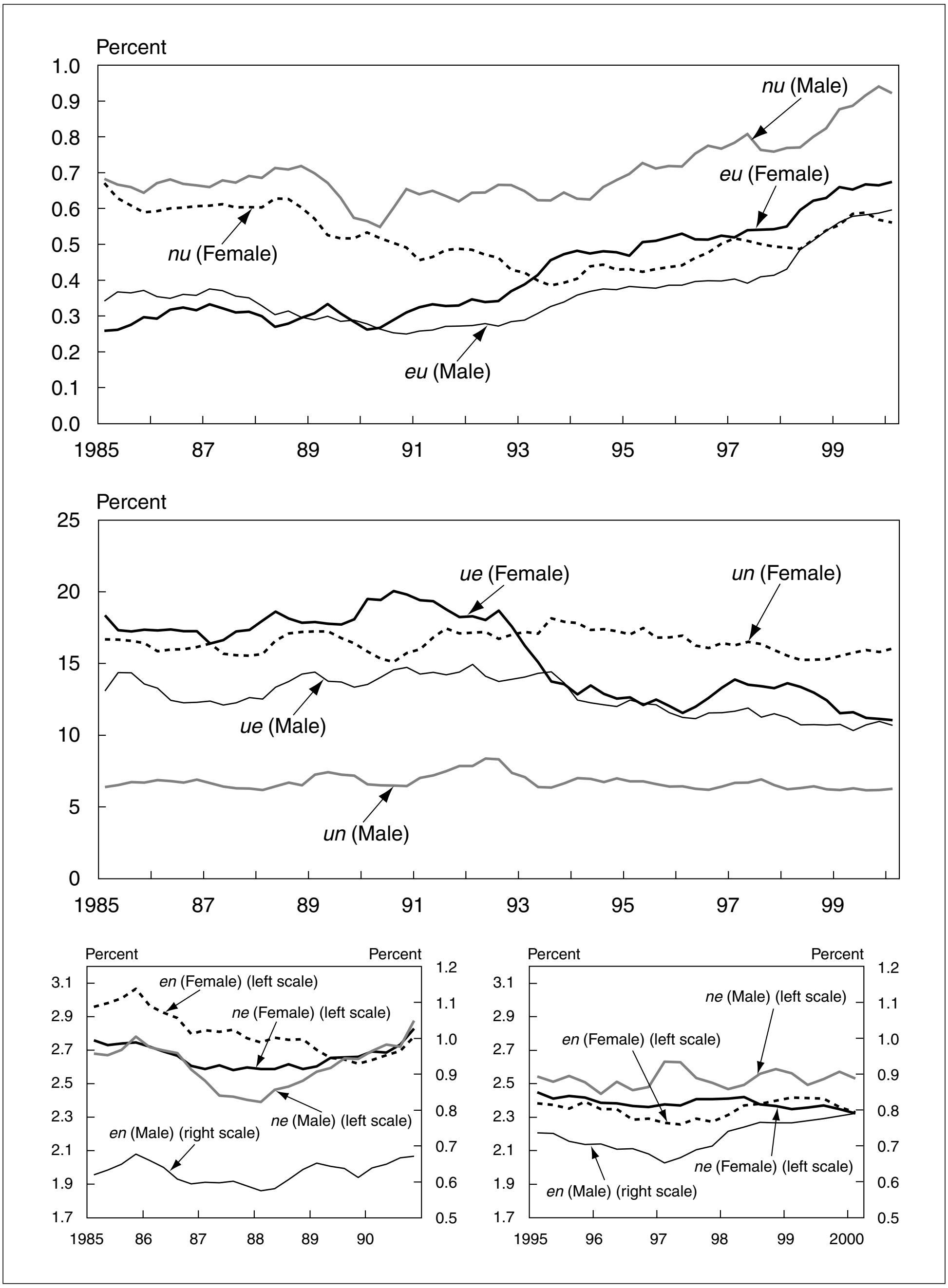


Figure 4 Transition Probabilities



during the second half of the 1990s seems to have been shifted downward from that of the second half of the 1980s.

To take a closer look, Table 2 provides the transition probabilities at five-year intervals beginning in the first quarter of 1985 and covering the first quarter of 1990, the first quarter of 1995, and the first quarter of 2000.

Table 2 Transition Probabilities

Percent

	Total				Male				Female			
	1985	90	95	2000	1985	90	95	2000	1985	90	95	2000
ee	98.15	98.28	98.18	97.96	99.04	99.08	98.88	98.61	96.78	97.10	97.15	97.00
eu	0.31	0.27	0.42	0.63	0.34	0.28	0.38	0.60	0.26	0.26	0.47	0.67
en	1.55	1.45	1.40	1.42	0.62	0.64	0.74	0.79	2.96	2.64	2.38	2.33
ue	15.22	16.04	12.53	10.82	13.09	13.53	12.45	10.68	18.36	19.51	12.64	11.06
uu	74.26	73.52	76.44	79.12	80.54	79.91	80.78	83.06	64.96	64.66	70.32	72.90
un	10.53	10.44	11.02	10.06	6.37	6.56	6.78	6.26	16.68	15.83	17.03	16.04
ne	2.74	2.69	2.47	2.38	2.68	2.69	2.54	2.53	2.76	2.69	2.45	2.32
nu	0.67	0.54	0.51	0.67	0.68	0.56	0.70	0.92	0.67	0.53	0.43	0.56
nn	96.59	96.76	97.02	96.95	96.64	96.74	96.76	96.55	96.57	96.77	97.12	97.12

Let us first look at the transition probability from employment (rows 3 through 5: *ee*, *eu*, *en*). The probability of remaining employed over two consecutive months (*ee*) rose for both men and women from 1985 (the period of recession caused by the appreciation of the yen) to the bubble period in 1990, and declined in 2000. The decline in the probability of employment during 1990s can be explained by the flow into the unemployment pool (*eu*) and exit from the labor force (*en*). Viewed in time series, it becomes clear that a particularly marked change occurred in the case of women. In 1985, among all women who did not remain employed (0.26 + 2.96 = 3.22 percent), approximately 90 percent (2.96/3.22 = 0.919) exited the labor force. By 2000, this ratio had dropped to the 70 percent range (2.33/(2.33 + 0.67) = 0.777), indicating that a growing ratio of women leaving their jobs were joining the unemployment pool. It should be noted, however, that the ratio of women exiting the labor force remained overwhelmingly higher than the ratio for men.

Next, a review of the flow from unemployment (rows 6 through 8: *ue*, *uu*, *un*) shows that the transition probability from unemployment to employment (*ue*) temporarily rose for both men and women during the bubble period but thereafter declined. This downward trend can be particularly observed for women. With the declining probability of employment, the number of unemployed persons failing to find employment increased. The probability of remaining in the unemployment pool (*uu*) increased around the year 2000, while the ratio of persons giving up their search for jobs and exiting the labor force (*un*) declined.

Finally, the transition probability from not-in-the-labor-force (rows 9 through 10: *ne*, *nu*, *nn*) reveals the following. Viewed in time series, the transition rate of workers moving directly from not-in-the-labor-force to employment with no intermediate stop in the unemployment pool (*ne*) has been declining since 1990. However, a difference of behavior is observed between men and women in the exit from the labor force. In the case of men, the transition probability from not-in-the-labor-force to employment (*ne*) has declined, and in 1995 and 2000 an increased probability from not-in-the-labor-force to the unemployment pool is observed (increase in *nu* for men). Furthermore, the probability of remaining in not-in-the-labor-force (*nn*) also declined for men in 2000, indicating an added worker effect. On the other hand, in the case of women, the probability of remaining in not-in-the-labor-force (*nn*) increased in both 1990 and 1995. This can be interpreted to mean that, during this period, an increasing number of women chose to remain in not-in-the-labor-force (delayed entry effect) instead of entering the labor force given the low possibility of finding a job. However, in 2000, the drop in the *ne* flow was canceled out by the flow to the unemployment pool (increased *nu* flow).

Based on these flow observations, higher unemployment rates in the post-bubble period can be explained as follows. While the transition probabilities from employment to unemployment (*eu*) increased and the transition probabilities from unemployment to employment (*ue*) dropped sharply, the flow from unemployment to not-in-the-labor-force declined (*un*) for both men and women. Therefore, it can be said that there has been a pileup of the unemployed in the unemployment pool. On the other hand, while the transition probability from not-in-the-labor-force to employment (*ne*) has been declining, in the case of men, the transition probability from not-in-the-labor-force to unemployment (*nu*) has increased. In 2000, a similar trend was observed for women as well. In other words, it can be seen that upward pressure on the unemployment rate was also being exerted from the increasing flows from not-in-the-labor-force to the unemployment pool.

Next, I attempted a quantitative verification by calculating how the determinants of the changes in the rate of unemployment can be explained by each of the flows. The results are shown in Tables 3 and 4.[15] The steady-state rate of unemployment appearing in these tables is the rate of unemployment derived under the assumption that the nine transition probabilities for 1985, 1990, 1995, and 2000 in Table 2 remain unchanged in the future (referred to here as the "steady state"). From the table, we can see that the steady-state rates of unemployment (total) for 1985, 1990, 1995, and 2000 were 2.52 percent, 2.03 percent, 2.96 percent, and 4.80 percent, respectively. The steady-state rates of unemployment for men and women are also shown in the same table.

For reference, the actual unemployment rate at each period is also reported at the bottom of the Table 3. As can be seen, the steady-state unemployment rates calculated in this paper are quite close to the actual rates.

Also in Tables 3 and 4, I attempted several patterns of calculations to see which of the changes in the elements of the transition matrices can account for the secular rise in unemployment. The calculations were carried out as follows. First, I allow one or more elements of interest in the 1985 transition matrix to take their values in the 1990 transition matrix. Then, the steady-state rate of unemployment was calculated from this newly formed transition matrix. The fraction of the overall change in the

15. The computational methods for Tables 3 and 4 can be summarized as follows. First, assume that a worker moves from his state at time t to another state at time $t + 1$ according to the nine transition probabilities shown in Table 2. For the sake of simplification, this relation is expressed as $X(t + 1) = P(t)X(t)$, where $X(t)$ is the 3×1 vector for the three states of E, U, and N at time t, and $P(t)$ is the 3×3 matrix expressing the nine transition probabilities. Assuming that $P(t)$ maintains a constant transition rate P over time, the state at time $m + 1$ can be expressed as $X(m + 1) = P^m X(0)$. If we assume here that P is an ergodic Markov chain, there is only one vector X^* that can satisfy the relation $X^* = PX^*$ when $m \to \infty$. The steady-state unemployment rate computed in this paper is calculated by obtaining X^*. See the Appendix for a detailed explanation of the computation method. The advantage of this method is that even if consecutive time-series data are not available, changes in unemployment can be decomposed by flow using data from two observation times.

steady-state rate of unemployment attributable to the change in any element(s) of the transition matrix is then estimated as the difference between the steady-state rate associated with the newly formed transition matrix and the rate for the 1985, divided by the total predicted change between the two periods.[16]

Table 3 Steady-State Unemployment Rate (1)

Percent

	1985	1990	Change in S-S rate	Percent explained	1990	1995	Change in S-S rate	Percent explained	1995	2000	Change in S-S rate	Percent explained
Steady-state rate of unemployment												
Total	2.52	2.03	−0.49	—	2.03	2.96	0.93	—	2.96	4.80	1.84	—
Male	2.50	2.01	−0.49	100	2.01	2.95	0.94	100	2.95	5.04	2.09	100
Female	2.58	2.07	−0.50	100	2.07	2.95	0.87	100	2.95	4.47	1.52	100
Male												
eu, *ue*, *nu*, *un*	2.50	2.00	−0.51	103	2.01	2.78	0.77	82	2.95	4.90	1.95	93
eu, *nu*	2.50	2.06	−0.45	90	2.01	2.65	0.64	68	2.95	4.32	1.37	66
eu	2.50	2.21	−0.30	60	2.01	2.50	0.49	52	2.95	4.01	1.06	51
nu	2.50	2.35	−0.15	30	2.01	2.17	0.16	17	2.95	3.26	0.31	15
ee, *en*, *eu**, *ne*, *nn*, *nu**	2.50	2.08	−0.42	85	2.01	2.81	0.80	85	2.95	4.45	1.50	72
ee, *nn*	2.50	2.50	0.00	1	2.01	2.07	0.06	6	2.95	3.00	0.05	2
en, *ne*	2.50	2.51	0.01	−2	2.01	2.09	0.08	9	2.95	2.99	0.04	2
Female												
eu, *ue*, *nu*, *un*	2.58	2.16	−0.41	83	2.07	2.88	0.80	92	2.95	4.35	1.41	92
eu, *nu*	2.58	2.21	−0.37	74	2.07	2.39	0.32	37	2.95	3.99	1.04	68
eu	2.58	2.58	0.00	0	2.07	2.64	0.56	64	2.95	3.58	0.63	41
nu	2.58	2.21	−0.37	74	2.07	1.83	−0.24	−28	2.95	3.36	0.41	27
ee, *en*, *eu**, *ne*, *nn*, *nu**	2.58	2.10	−0.47	95	2.07	2.44	0.37	43	2.95	4.08	1.13	74
ee, *nn*	2.58	2.51	−0.06	12	2.07	2.13	0.05	6	2.95	3.01	0.06	4
en, *ne*	2.58	2.50	−0.07	14	2.07	2.08	0.01	1	2.95	2.99	0.04	3
Actual unemployment rate												
Total	2.57	2.13			2.13	3.00			3.00	4.80		
Male	2.57	2.10			2.10	2.98			2.98	4.98		
Female	2.58	2.17			2.17	3.04			3.04	4.53		

Note: Asterisk denotes cases in which changes made in two elements contained in the line resulted in a change in the remaining element. Absence of an asterisk indicates cases in which only the indicated transition probability has been changed.

16. In this method, only the transition probabilities of a certain element(s) of the transition matrix are replaced with those from other points in time. Hence, the sum of each row of the transition matrix does not necessarily become one. As the object of the analysis here is to identify the transition probabilities whose changes contribute to changes in the unemployment rate, I have analyzed cases in which only a certain element(s) is changed. This implies the possibility that the transition matrix may not be a Markov chain, in which case there may be certain instances in which the condition "one of the eigenvalues is one," which is necessary for the computation of the steady-state unemployment rate, is not met. Whenever this happened, I used the eigenvalue closest to one to complete the computations. Note that in none of the cases did I obtain an eigenvalue that was significantly different from one. From this, I surmised that errors caused by the fact that the matrix does not add up to one were not very large.

Table 4 Steady-State Unemployment Rate (2)

Percent

	1985	1990	Change in S-S rate	Percent explained	1990	1995	Change in S-S rate	Percent explained	1995	2000	Change in S-S rate	Percent explained
Steady-state rate of unemployment												
Total	2.52	2.03	–0.49	—	2.03	2.96	0.93	—	2.96	4.80	1.84	—
Male	2.50	2.01	–0.49	100	2.01	2.95	0.94	100	2.95	5.04	2.09	100
Female	2.58	2.07	–0.50	100	2.07	2.95	0.87	100	2.95	4.47	1.52	100
Male												
*ue, un, uu**	2.50	2.42	–0.09	17	2.01	2.11	0.10	11	2.95	3.34	0.39	19
ue	2.50	2.49	–0.01	3	2.01	2.02	0.01	2	2.95	2.97	0.02	1
uu	2.50	2.42	–0.09	18	2.01	2.11	0.10	11	2.95	3.34	0.39	19
un	2.50	2.51	0.00	0	2.01	2.02	0.01	1	2.95	2.94	–0.01	0
Female												
*ue, un, uu**	2.58	2.53	–0.05	10	2.07	2.51	0.44	50	2.95	3.23	0.28	18
ue	2.58	2.57	–0.01	1	2.07	2.12	0.04	5	2.95	2.96	0.01	1
uu	2.58	2.56	–0.02	4	2.07	2.45	0.37	43	2.95	3.22	0.28	18
un	2.58	2.57	0.00	1	2.07	2.08	0.00	1	2.95	2.94	–0.01	–1

Note: Asterisk denotes cases in which changes made in two elements contained in the line resulted in a change in the remaining element. Absence of an asterisk indicates cases in which only the indicated transition probability has been changed.

Let us begin by examining how changes in the probability of inflow into the unemployment pool affect changes in the rate of unemployment (Table 3). Looking at the changes occurring between 1985 and 1990, in the case of men, we observe that 90 percent of the decline in the unemployment rate can be explained by the decline in the probability of inflow into the unemployment pool (*eu* and *nu*). Of this 90 percent, 60 percent is accounted for by the decline in *eu*, while 30 percent is accounted for by the decline in *nu*. Thus, the inflow into the unemployment pool was reduced from both the employment and not-in-the-labor-force sides. In the case of women, for the same period, 74 percent of the decline in the unemployment rate can be explained by the decline in the inflow into the unemployment pool. However, unlike in the case of men, this can be totally attributed to the decline in the *nu* flow. During the bubble period, because of tight labor market conditions, people were able to move directly from not-in-the-labor-force to employment with no intermediate stop in the unemployment pool. This may have contributed to the further reduction in the unemployment rate, especially that of females.

Next, let us take a look at changes occurring between 1990 and 1995. During this period, differences between men and women can also be observed. In the case of men, both the *eu* and *nu* transition probabilities increased and contributed to a rise in the unemployment rate. For women, on the other hand, the rise in the *eu* flow accounts for 64 percent of the rise in the unemployment rate. But this is counteracted by a decline in the *nu* flow, which suppresses the unemployment rate (28 percent). As observed in Table 2, there was a sharp increase in the loss of jobs among employed women in 1995. With the rapid deterioration of labor market conditions, women chose to stay out of the labor force instead of joining the unemployment pool.

This behavior of delaying entry into the labor force acted to suppress the rise in the unemployment rate.

However, it can be observed that this type of behavior by women began to change as the recession became prolonged. Examining the changes that occurred between 1995 and 2000, we can see that the *eu* flow of women continued to exert upward pressure on unemployment rates. At the same time, the increased flow from not-in-the-labor-force to unemployment (*nu*) was responsible for 27 percent of the increase in the unemployment rate.

Thus, the movement of women between unemployment and not-in-the-labor-force contains elements of both a delayed entry effect and an added worker effect. Which of these two effects had a greater impact on changes in the unemployment rate? The results obtained above suggest that the answer to this question varies according to the economic conditions that prevailed at the various points of observation.

Finally, let us observe the transition probabilities for outflows from the unemployment pool (*ue*, *uu*, *un*; Table 4).

At all points of observation, the flow from unemployment to employment (*ue*) and the transition flow from unemployment to not-in-the-labor-force (*un*) have very minor explanatory powers. In other words, judging from the analysis of Table 4, the impacts of the drop in the transition probability from unemployment to employment, and the transition of discouraged job seekers from unemployment to not-in-the-labor-force are unlikely to have had a significant effect on changes in unemployment rates. It cannot be denied that these results are somewhat unexpected, particularly in light of the fact that, while no major changes were observed in *un*, in both Figure 4 and Table 2 we observed a rapid decline in *ue* after 1990. It is possible that my computations are unable to distinguish between the reduced flow from unemployment to employment (*ue*), and the increase in the number of people remaining in the unemployment pool (*uu*) because of failure to find jobs.

Nevertheless, the picture is much clearer when *ue*, *uu*, and *un* are integrated for making the following overall judgment concerning the rise in the unemployment rate in the 1990s. While outflows from the unemployment pool to both employment (*ue*) and not-in-the-labor-force (*un*) were subdued during the 1990s, the growing probability of people remaining in the unemployment pool became an important factor for pushing unemployment rates upward.

B. Incidence and Duration of Unemployment

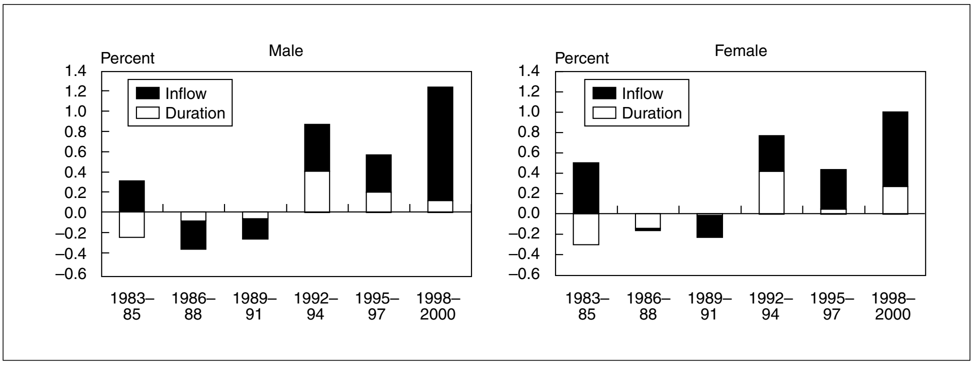
The findings of Section III.A indicated the possibility that the rising probability of both *eu* and *un*, and also the rising probability *uu* (longer unemployment duration) may have contributed to the secular rise in the unemployment rate during the 1990s. Following on this finding, in Section III.B I attempt to determine which of these two factors (unemployment incidence and duration) had a stronger impact on changes in the rate of unemployment during 1983–2000. The methodology used here differs from that of Tables 2–4 in that we will not be able to determine whether unemployment is being generated by inflows into the unemployment pool from employment or from not-in-the-labor-force. Nor will we be able to determine whether unemployment is terminated by movements to which of these two states.

However, the methodology used here will allow us to observe changes in each phase throughout the time series. This will make it possible to supplement the preceding analysis, which was restricted to comparisons of four points in time due to data limitations.

In the steady state, unemployment is the product of unemployment duration and inflows. In Figure 5, the period between 1983 and 2000 is divided into three-year segments and the contributions of unemployment duration and inflows to changes in the rate of unemployment are shown for each time segment.[17] For each segment, the sum of the contributions of the unemployment duration and unemployment inflow is equal to the total change in the rate of unemployment.

Figure 5 clearly shows that the principal factor contributing to changes in the unemployment rate differs from one time segment to another. Let us first start with the 1983–85 segment, a period when both men and women experienced rising unemployment rates. As the unemployment duration was dropping during this segment, rising unemployment can be attributed to unemployment inflow: that is, a rapid increase of inflow into the unemployment pool. Moving to the next segment of 1986–88, this was a period of declining unemployment rates for both men and women. The principal contributing factor for men was the drop in unemployment inflow, while for women it was the drop in unemployment duration. During 1989–91, when unemployment rates declined even further, the principal contributing factor was the decline in unemployment inflow. This result is consistent with the interpretation

Figure 5 Contributions of Changes in Unemployment Inflow and Duration to Changes in Unemployment Rate



17. Assume a steady-state unemployment rate where the volume of flows in and out of the states of employment, unemployment, and not-in-the-labor-force are identical. Given a monthly inflow into the unemployment pool, $F(= EU + NU)$, and an average unemployment duration per completed unemployment spell, $D(= 1/(ue + un)$, the stock unemployment figure U can be expressed as $U = F \times D$. By dividing both sides by the labor force population, the left-hand side becomes the unemployment rate (u). If F' is inflow divided by the labor force population, the unemployment rate can be expressed as $u = F' \times D$. The change in unemployment rate between time 1 and time 2 ($\Delta u = u_2 - u_1$) can be decomposed and written as $\Delta u = F_1'(D_2 - D_1) + D_2(F_2' - F_1')$. This equation shows that changes in the rate of unemployment can be explained by changes in the duration of unemployment (first term on the right-hand side) and changes in unemployment inflow (second term). In addition to this method, Tachibanaki (1984) and Mizuno (1992) have examined in detail other possible methods of estimating unemployment duration using Japanese data. According to these prior studies, all available methods require certain assumptions to be made, so that the estimation results obtained must be viewed with a degree of flexibility.

of this paper that the inflow into the unemployment pool from both employment and not-in-the-labor-force declined during this period.

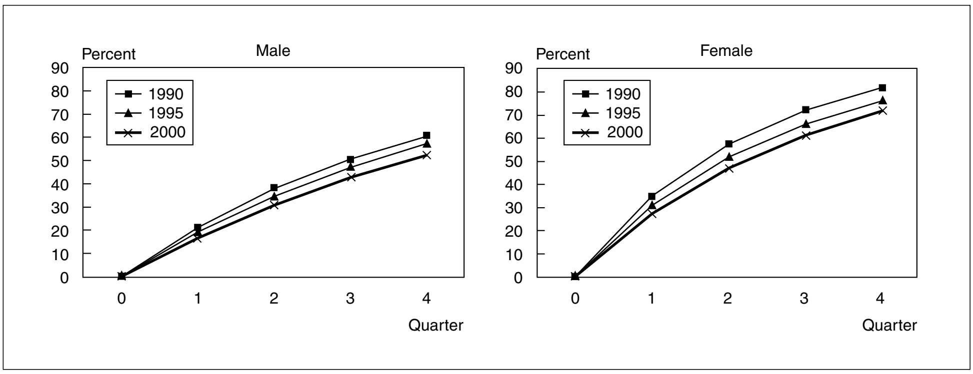
During 1992–94, after the bubble burst, both unemployment inflow and unemployment duration contributed to rising unemployment rates. However, the impact of unemployment inflow was slightly stronger for men, while the impact of unemployment duration was slightly stronger for women. This development is reversed in the 1995–97 segment, when the rise in the unemployment rate for women can be almost totally explained by the growing unemployment inflow. When unemployment rates jumped sharply during 1998–2000, unemployment inflow was the principal contributing factor for both men and women.

It has long been said that one of the features of the Japanese labor market, as compared to that of the United States, Canada, and other countries, is Japan's relatively low incidence of unemployment combined with a relatively long duration of unemployment.[18] However, the results of this paper indicate that the rising incidence of unemployment (inflow into the unemployment pool) has had a major impact on the rising rate of unemployment, particularly after the mid-1990s. Combined with a relatively high duration of unemployment compared to other countries, Japan is now experiencing a serious condition in which growing numbers of job seekers accumulating in the unemployment pool are finding it very difficult to exit the pool.

Figure 6 depicts the incidence of outflow from the unemployment pool over time as observed in 1990, 1995, and 2000.

The graph lines show how long and at what probability someone who has lost his job can expect to exit the unemployment pool.[19] The loss of job occurs at time 0 (at which point the probability of outflow from the unemployment pool is 0 percent). Thereafter, the graph depicts the probability of exiting the unemployment pool over four consecutive quarters.

Figure 6 Exit Probability from the Unemployment Pool



18. For instance, see Mizuno (1982) and Higuchi (2001).
19. The probability that a person unemployed at time t will remain unemployed in the following quarter is uu_{t+1}. The probability that a person unemployed at $t + 1$ will remain unemployed in the following quarter, that is, the second quarter, is $uu_{t+1} \times uu_{t+2}$. The probabilities for the third and fourth quarters are $uu_{t+1} \times uu_{t+2} \times uu_{t+3}$, and $uu_{t+1} \times uu_{t+2} \times uu_{t+3} \times uu_{t+4}$. Thus, the probabilities of continued unemployment can be computed as the product of uu. The exit probability can be obtained by deducting the probability of continued unemployment from one.

Figure 6 reveals a flattening of the exit probability line over the period of 1990, 1995, and 2000, indicating that unemployed persons were experiencing increased difficulty in exiting the unemployment pool during the 1990s. For the year 2000, in the case of men, we can see from the figure that the probability of exiting the unemployment pool within one year is 52 percent. This can be interpreted to mean that nearly one-half of all unemployed men have been unemployed for at least one year. The one-year exit incidence for women in 2000 was considerably higher than for men and stood at 72 percent. This can be interpreted to mean that women exit the unemployment pool at a higher incidence than men.[20] However, between 1990 and 2000, women experienced a sharper drop in exit incidence than men. This points to a growing accumulation of unemployed women in the unemployment pool as well.

IV. Analysis Using Flow Data: Part 2

The analysis in Section III showed that flow data have exhibited diverse movements at various points in time, and that they contain a great deal of useful information that cannot be obtained solely from observing the changes in the unemployment rate. However, as outlined in Section II.B, few studies have examined the relation between flow data and business cycles. In particular, for Japan, the only existing research consists of the series done by Mizuno. Moreover, Mizuno's analysis is focused exclusively on determining the effectiveness of flow data in explaining the changes in the unemployment rate.

In this subsection, I attempt an empirical analysis of the relation between movements in flow data and macroeconomic variables.[21] In Section IV.B, I will employ a vector autoregression (VAR) model to examine the properties of flow data as an information variable. Then in Section IV.C, I will apply the approach of Bleakley *et al.* (1999) to the case of Japan and attempt to improve the forecasting power of the Phillips curve by using flow data.

The objective of the following analysis is to present an example of the usefulness of flow data for future research, and to illustrate how flow data can provide additional information that can supplement prior research.

A. Preliminary Analysis

I will begin by observing the properties and correlation between various flow data and the unemployment rate and other economic indicators, and data on price and wage levels.

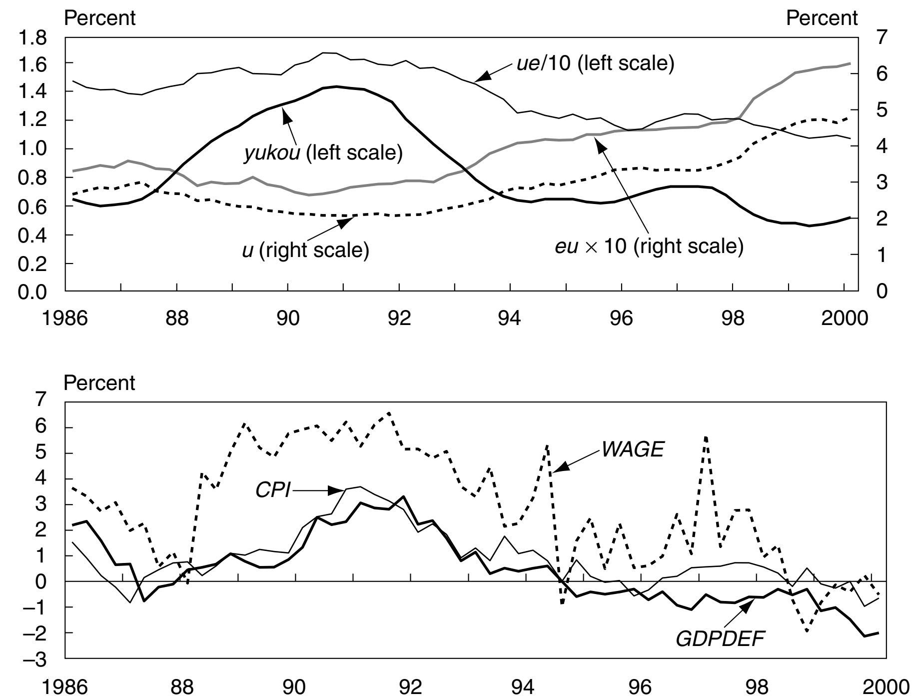
20. This is probably because women are more likely to exit the unemployment pool by leaving the labor force than men, and while women have a higher incidence of unemployment, they also have a higher incidence of employment because of the availability of part-time employment opportunities.

21. Continuous data for flows between employment and not-in-the-labor-force (*en* and *ne*) are unavailable for the entire period of the study, and only partial samples are available at certain points. Hence, the data used in the empirical analysis of this paper are limited to the four types of flow data between unemployment and employment, and between unemployment and not-in-the-labor-force (*ue*, *eu*, *un*, *nu*). Therefore, it should be noted that this analysis does not necessarily constitute a comprehensive analysis of the dynamics of the labor market.

Figure 7 plots the following time series: unemployment rate (*u*); the effective ratio of job offers to applicants (*yukou*); the sum of male-female *eu* and *ue* flows (to align the scales, *ue* and *eu* flow is multiplied by 0.1 and 10, respectively); and the year-on-year percentage changes in consumer price index (general) (*CPI*), GDP deflator (*GDPDEF*), and hourly total cash earnings (*WAGE*).[22]

In Figure 7, the unemployment rate and other variables appearing in the top seem to fluctuate pro-cyclically. This also applies to the price-related variables appearing in the bottom graph until the mid-1990s. However, when it comes to the second half of the 1990s, these three price-related variables do not necessarily follow parallel trends. The trend in wage data is particularly notable. Even when business conditions deteriorated further at the end of the decade, wage data continued to show year-on-year positive growth, marking a major deviation from the GDP deflator trend that had been consistently negative after the mid-1990s. One of the possible reasons for this is that it reflects the downward rigidity in nominal wages.

Figure 7 Trends in Variables



Sources: Ministry of Health, Labour and Welfare, *Monthly Labour Survey* (various issues), *Report on Employment Service* (various issues); Statistics Bureau and Statistics Center, *Labour Force Survey* (various issues), *Consumer Price Index* (various issues); Cabinet Office, *National Accounts* (various issues).

22. The effect of the introduction and rate hike of consumption tax in 1989 and 1997, respectively, had been adjusted both with CPI and the GDP deflator.

Let us now take a closer look at the relation between these variables. The top two panels of Table 5 presents the mean and standard deviation for flow data and other variables. The variables of Table 5 are the same ones as in Figure 7 plus the following:

Table 5 Basic Statistics, Correlation Matrix, and Time Correlations

Basic statistics

	CPI	*GDPDEF*	*WAGE*	*u*	*ugap*	*yukou*	*gdpgap1*	*gdpgap2*
Mean	0.892	0.460	2.847	2.949	0.370	0.848	–4.256	–5.680
Std. dev.	1.098	1.290	2.301	0.791	0.413	0.314	1.875	2.226

	ue	*eu*	*un*	*nu*	*mue*	*meu*	*mun*	*mnu*	*fue*	*feu*	*fun*	*fnu*
Mean	13.808	0.390	10.751	0.567	12.662	0.365	6.740	0.704	15.441	0.427	16.463	0.509
Std. dev.	1.888	0.103	0.625	0.062	1.331	0.092	0.518	0.088	2.879	0.128	0.767	0.069

Correlation

	CPI	*GDPDEF*	*WAGE*	*ue*	*eu*	*un*	*nu*	*u*	*ugap*	*yukou*	*gdpgap1*	*gdpgap2*
CPI	1.000	—	—	—	—	—	—	—	—	—	—	—
GDPDEF	0.835	1.000	—	—	—	—	—	—	—	—	—	—
WAGE	0.735	0.752	1.000	—	—	—	—	—	—	—	—	—
ue	0.776	0.873	0.815	1.000	—	—	—	—	—	—	—	—
eu	–0.663	–0.803	–0.778	–0.931	1.000	—	—	—	—	—	—	—
un	0.419	0.475	0.526	0.433	–0.487	1.000	—	—	—	—	—	—
nu	–0.459	–0.358	–0.367	–0.255	0.376	–0.659	1.000	—	—	—	—	—
u	–0.713	–0.806	–0.802	–0.908	0.979	–0.617	0.531	1.000	—	—	—	—
ugap	–0.757	–0.774	–0.839	–0.906	0.950	–0.575	0.491	0.971	1.000	—	—	—
yukou	0.835	0.770	0.815	0.873	–0.786	0.407	–0.314	–0.795	–0.889	1.000	—	—
gdpgap1	0.737	0.700	0.810	0.789	–0.788	0.308	–0.311	–0.779	–0.866	0.892	1.000	—
gdpgap2	0.782	0.765	0.784	0.873	–0.870	0.345	–0.287	–0.855	–0.925	0.941	0.915	1.000

	CPI	*GDPDEF*	*WAGE*	*yukou*	*mue*	*meu*	*mun*	*mnu*	*fue*	*feu*	*fun*	*fnu*
mue	0.773	0.820	0.802	0.828	1.000	—	—	—	—	—	—	—
meu	–0.714	–0.789	–0.794	–0.800	–0.896	1.000	—	—	—	—	—	—
mun	0.507	0.610	0.593	0.519	0.578	–0.568	1.000	—	—	—	—	—
mnu	–0.616	–0.744	–0.676	–0.635	–0.774	0.898	–0.477	1.000	—	—	—	—
fue	0.710	0.839	0.755	0.830	0.812	–0.815	0.478	–0.697	1.000	—	—	—
feu	–0.569	–0.770	–0.712	–0.723	–0.806	0.882	–0.436	0.814	–0.927	1.000	—	—
fun	0.132	0.163	0.274	0.141	0.434	–0.394	0.502	–0.354	–0.036	–0.136	1.000	—
fnu	–0.249	–0.052	–0.099	–0.057	–0.174	0.211	–0.257	0.280	0.277	–0.234	–0.549	1.000

Time correlation

	ue	*mue*	*fue*	*eu*	*meu*	*feu*	*un*	*mun*	*fun*	*nu*	*mnu*	*fnu*
CPI	0.776 (0)	0.773 (0)	0.710 (0)	–0.663 (0)	–0.714 (0)	–0.569 (0)	0.646 (–4)	0.717 (–3)	0.651 (–12)	–0.547 (–7)	–0.616 (0)	–0.503 (–12)
GDPDEF	0.873 (0)	0.820 (0)	0.839 (0)	–0.803 (0)	–0.789 (0)	–0.770 (0)	0.586 (–3)	0.680 (–2)	0.676 (–11)	–0.585 (–13)	–0.744 (0)	–0.453 (–11)
WAGE	0.815 (0)	0.802 (0)	0.755 (0)	–0.778 (0)	–0.794 (0)	–0.712 (0)	0.555 (–11)	0.607 (–2)	0.581 (–12)	–0.558 (–5)	–0.710 (–2)	–0.446 (–15)

Note: Figures were shadowed when the null hypothesis of the zero correlation was not rejected at the 5 percent significance level.

the gap between the unemployment rate and the equilibrium unemployment rate (*ugap*: *White Paper on Labour Economics*, estimated by the Ministry of Health, Labour and Welfare); output gap (*gdpgap1*: non-manufacturing utilization rate fixed version; *gdpgap2*: non-manufacturing utilization rate estimated version)[23]; and, flow data (transition rate for male and female are identified by *m* and *f* appearing at the beginning of the term).

As in the case of Figure 7, the period covered extends from the first quarter of 1986 through the first quarter of 2000. Monthly data have been converted to a quarterly basis by taking a simple average. A review of the standard deviations of variables other than price-related variables shows that the output gap and *ue* flow are subject to larger changes than other variables. In particular, among the flow variables, the *ue* flow for women (*fue*) exhibits a large standard deviation value.

Next, let us examine the correlation between price variables and the various flow data. As shown in the third panel of Table 5, a positive relation is observed between the flow from unemployment to employment (*ue*) and price variables. Furthermore, this correlation is relatively stronger than the correlation between other stock variables and price and wage data. Also, a relatively strong negative correlation is observed between the flow from employment to unemployment (*eu*) and price and wage data. On the other hand, in comparison to the relation between flows between employment and unemployment and price and wage data, the relation between *un* and *nu* flows and price variables does not exhibit a higher level of correlation. In particular, the correlation with the flow from not-in-the-labor-force to unemployment (*nu*) is weak.

In Section III, we observed that flows between unemployment and not-in-the-labor-force differed for men and women. Given the possibility that these differences may be canceling each other out in the aggregated data, I computed the correlation between decomposed flows of men and women and the other variables. The computation results appear in the fourth panel of Table 5 and can be summarized as follows.

For men, there is a relatively strong correlation between the flows between employment and not-in-the-labor-force (*mnu*, *mun*) and prices. By contrast, the correlation coefficients for the flows for women (*fnu*, *fun*) and prices are extremely small. This indicates that the weak correlation between aggregated flows between unemployment and not-in-the-labor-force (*un*, *nu*) and prices results from the characteristics of the flows of women. As observed in Table 2, one of the reasons for this may be that the point at which the delayed entry effect is observed and the point at which the added worker effect is observed are intermixed in women's *nu* flow.

Finally, given the possibility that a lagged correlation may exist among the flow data and the various variables, I have computed the time correlation between the price and wage data and the various flow variables. Peak values of correlation coefficients are shown in the lowest panel of Table 5, and the number of lags at peak time appear in parentheses. A minus sign appearing in the parentheses with the number of lags indicates

23. See Kamada and Masuda (2001) for details of computation method. I thank Koichiro Kamada (Bank of Japan) for letting me use his data for the analysis in this paper.

that price and wage data are leading. For instance, –3, which appears in the *GDPDEF* and *un* intersection, indicates that the strongest correlation exists between the current *un* value and the GDP deflator from three quarters earlier. A zero appearing in the parentheses indicates the strongest correlation exists at concurrent values.

The results shown in the lowest panel of Table 5 indicate that the strongest correlations between *ue* and *eu* flows and price and wages exist at concurrent values. This holds for both men and women taken separately, as well as when aggregated. On the other hand, prices and wages are observed to be leading in relation to flows between unemployment and not-in-the-labor-force. This is particularly true in the case of the flow of women (*fun*, *fnu*), where prices and wages lead by approximately three years. However, given this extremely protracted lag, it is not evident whether a clear relation exists between these variables. Regarding these time correlation results, what can be said, at least in the case of men, is that the flow from not-in-the-labor-force to unemployment increases (decreases), and the flow from unemployment to not-in-the-labor-force decreases (increases) within 0–3 quarters of a decline (rise) in prices and wages. While the reservation must be made that these correlation coefficients by themselves cannot confirm a specific causal relation, these results are consistent with the hypothesis that the added worker effect does exist for men.

B. Application of VAR to the Flow Data

Next, I estimate a simple VAR model to observe the causal relation between price variables and the flow data. Here, I use the GDP deflator as the price variable.[24] VAR was applied to the five variables, *GDPDEF*, *eu*, *ue*, *un*, and *nu*. Furthermore, in light of the correlation results observed in Sections III and IV.A, which indicated a difference in flows between men and women, I also estimated VAR separately for the flow of men and women using (*GDPDEF*, *meu*, *mue*, *mun*, *mnu*) and (*GDPDEF*, *feu*, *fue*, *fun*, *fnu*).[25] The period covered extends from the first quarter of 1986 to the first quarter of 2000. In addition to the five variables, I adopted a constant term. I chose a lag term of one based on AIC criteria.[26]

Granger's causality test results for these estimations are summarized below. The null hypothesis is that a certain variable does not Granger cause another variable.

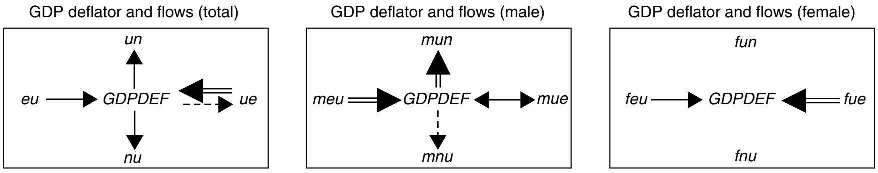
24. As shown in Figure 7, year-on-year changes of CPI and wages continued to record positive even after economic conditions deteriorated in the second half of the 1990s. I opted to use the GDP deflator as the price variable since, in comparison with CPI and wages, the GDP deflator showed greater flexibility in movement during the second half of the 1990s. Note that in the analysis of forecasting below, I have used CPI and wages in addition to the GDP deflator.

25. As the labor market is not completely divided for men and women, it would be better to combine the flows for men and women in estimating the VAR. However, because of the limited number of samples available, I have estimated them separately in this paper.

26. It should be noted that the flow data used in this paper may be I(1) (the ADF test showed that, with the exception of *yukou*, all variables used in Table 5 had the possibility of being I(1)). Therefore, in this VAR analysis, I have followed the method of Toda-Yamamoto (1995) and added one lag term to the optimal lag term. In principle, all data used in VAR must be stationary, and the need arises to pretest the data to determine whether the data contain unit roots. However, various unit root tests have been shown to have limited testing powers, so that pretest results may be biased. In addition, when data are shown to be I(1), the general process taken for the VAR is to take the differential to make I(1) data stationary. However, such a process may fail to yield good results, because important information has been removed. Toda and Yamamoto (1995) have proposed a method for avoiding such problems. Note that the results of my analysis did not differ significantly when one or two lag terms were used.

The double, single, and dashed lines in Figure 8 respectively denote that the null hypothesis can be rejected at the 1 percent, 5 percent, and 10 percent levels of significance.[27]

Figure 8 Granger's Causality Test



Note: The double, single, and dashed lines respectively denote that the null hypothesis can be rejected at the 1 percent, 5 percent, and 10 percent levels of significance.

The null hypothesis that the flow from employment to unemployment (*eu*, *meu*, *feu*) and the flow from unemployment to employment (*ue*, *mue*, *fue*) does not Granger cause the GDP deflator can be rejected with a high level of significance. Likewise, the null hypothesis that the GDP deflator does not Granger cause the flow from unemployment to employment (*ue*, *mue*) is rejected.

On the other hand, no Granger causality is detected from the flow from unemployment to not-in-the-labor-force (*un*, *mun*, *fun*) and the flow from not-in-the-labor-force to unemployment (*nu*, *mnu*, *fnu*) to the GDP deflator. However, the null hypothesis that the GDP deflator does not Granger cause the flow from unemployment to not-in-the-labor-force (*un*, *mun*) and the flow from not-in-the-labor-force to unemployment (*nu*, *mnu*) is rejected. This implies that the flows between unemployment and not-in-the-labor-force are even more lagging than the price variables. It should be noted, however, that such relationships do not hold between the flows of women (*fun*, *fnu*) and the GDP deflator. As I have previously explained, this result can be attributed to the co-mingling of the discouraged worker effect, the added worker effect, and the delayed entry effect in the flows of women between unemployment and not-in-the-labor-force.

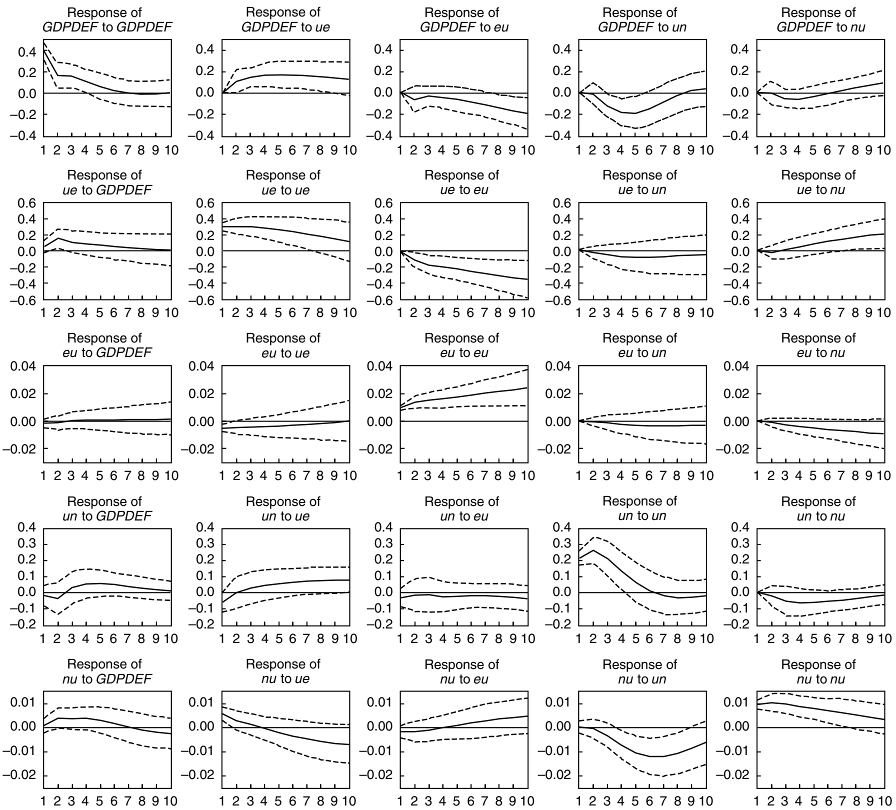
Turning next to Figure 9, the series of graphs show the impulse response of the GDP deflator and the aggregated flow data for men and women.

First of all, a one-standard-deviation *ue* shock induces the GDP deflator to rise gradually, while a one-standard-deviation *eu* shock causes the GDP deflator to decline over 10 quarters. Both responses follow paths that are generally consistent

27. Granger's causality test results among flow data are as follows:

		ue to *eu*	*eu* to *ue*	*nu* to *eu*	*eu* to *nu*	*un* to *eu*	*eu* to *un*	*nu* to *ue*	*ue* to *nu*	*un* to *ue*	*ue* to *un*	*un* to *nu*	*nu* to *un*
Total	*F*-value	1.129	4.900	1.222	3.922	0.244	1.942	1.789	5.116	1.410	4.304	6.792	0.571
	p-value	[0.332]	[0.011]	[0.303]	[0.026]	[0.784]	[0.154]	[0.178]	[0.010]	[0.254]	[0.019]	[0.002]	[0.569]
Male	*F*-value	0.108	3.294	0.796	8.074	0.098	2.576	3.479	6.498	0.069	6.974	1.991	3.115
	p-value	[0.898]	[0.045]	[0.457]	[0.001]	[0.906]	[0.086]	[0.038]	[0.003]	[0.933]	[0.002]	[0.147]	[0.053]
Female	*F*-value	0.815	2.671	0.654	1.308	0.485	0.412	1.349	1.574	0.249	0.782	2.310	0.553
	p-value	[0.448]	[0.079]	[0.524]	[0.279]	[0.619]	[0.664]	[0.269]	[0.217]	[0.781]	[0.463]	[0.110]	[0.579]

Figure 9 Impulse Response



Note: Dashed lines indicate the two standard deviation bands of each shock. Cholesky decomposition was undertaken, although changes in recursive order generally did not affect the result.

with expectations. Next, the response of the *ue* flow caused by a one-standard-deviation GDP deflator shock induces the *ue* flow to increase until it peaks out in the second quarter, and thereafter it gradually decays toward zero. This can be interpreted to mean that, in response to economic recovery and rising prices, the transition probability to unemployment from employment continues to climb over a period of 2–3 years. In contrast, a one-standard-deviation GDP deflator shock causes the *eu* flow to decrease slightly over the first to third quarters, but the impact of the shock virtually vanishes thereafter. This is somewhat consistent with the result obtained previously that no Granger causality was detected from the GDP deflator to the *eu* flow.

Returning to the response of *un* to a one-standard-deviation GDP deflator shock where Granger causality is clearly observed, the *un* declines temporarily until the second quarter and restarts on a mild climb thereafter. This response of temporal decline is the opposite of what was observed in the preceding graphs and in the time correlation analysis, and does not allow for ready interpretation. The response of the *nu* flow to GDP deflator shock induces an increase until its peak in the fourth quarter, but begins to decrease thereafter. The *nu* response after the seventh quarter may be interpreted to represent the downturn in the flow from not-in-the-labor-force to the unemployment pool after almost two years of economic recovery. However, the *nu* response of the earlier period is hard to interpret regarding the time correlation analysis. Therefore, no clear response pattern can be detected in this case, also.

The VAR analysis results are subject to some major data restrictions, such as the limited number of samples and the unavailability of continuous flow data for *en* and *ne*. Consequently, it is difficult to properly examine the robustness of the results. With the accumulation of further data, the necessary improvements in analytical tools remain a challenge for the future.

C. Application to Inflation Forecasting Using the Phillips Curve

Based on the results obtained thus far, it is difficult to reach a clear conclusion on the relation between flows between unemployment and not-in-the-labor-force, and business cycles or prices. However, VAR analysis and the correlation-time correlation results have provided compelling evidence of a strong relation between the flows between employment and unemployment and prices. Based on this fact, the possibility arises that information concerning the flows between employment and unemployment may be more useful in forecasting future price developments than the unemployment rate, which is an aggregation of all flow data. To test this idea, I have used flow data for flows between employment and unemployment (*ue*, *eu*) to forecast future price movements.

The inflation forecast function assumes a Phillips curve as follows.[28]

$$\pi_t = const. + \sum_{i=1}^{n} \alpha_i \pi_{t-i} + \beta_1 flow_{t-1} + \gamma_1 IMP_t + \varepsilon_t,$$

where π is the inflation rate (year-on-year rate of increase in the CPI, GDP deflator, and hourly total cash earnings), *const.* is the constant term, *flow* is the transition probability of *ue*, *eu*, etc. (aggregated; non-aggregated data for male and female were also used), *IMP* is import prices, ε is the error term, and subscript t indicates time. The lagged terms of the inflation rate, the second term on the right-hand side, were used as a proxy variable for the expected inflation rate (or inertia).[29] In determining the lag terms, I started with a sufficiently long lag term and chose the longest lag term when the last lag term shows its significance. For estimations using *WAGE* as a

28. For the recent studies regarding inflation forecast using the Phillips curve, see Fuhrer (1995), Gordon (1997), Stock and Watson (1999), and Fukuda and Keida (2001), for example.
29. In many instances of prior research, NAIRU has been estimated by using past inflation lag terms as the expected rate of inflation and adopting a function such that the sum of the coefficients is one. However, prior Japanese research indicates that the performance of estimation deteriorates when the restriction introduced on the sum of the coefficients equals one (Higo and Nakada [1999]). Therefore, in this analysis, I have not placed a restriction on the sum of the coefficients. To absorb the expected inflation rate and inertia, which cannot be fully supplemented by inflation lag terms, I also adopted the constant term. Using survey data as a proxy variable for the expected inflation rate under the Carlson-Parkin method is another possible option. But as improvement of the expected inflation variable is not the primary concern of this paper, I have followed conventional methods for the inflation expectation (Nakayama and Oshima [1999] and Fukuda and Keida [2001] are recent examples of using the Carlson-Parkin method and estimation of the Phillips curve based on those results).

dependent variable, I used the *CPI* lag term for the expected inflation rate. The period of estimation covers the period between the first quarter of 1986 and the first quarter of 2000.

For purposes of comparison, similar estimations were undertaken in cases where the unemployment rate (*u*), the gap between the unemployment rate and the equilibrium unemployment rate (*ugap*), the effective ratio of job offers to applicants (*yukou*), and the output gap (*gdpgap1*, *gdpgap2*) were used instead of flow data. To eliminate the simultaneous equation bias, all independent flow and other variables were shifted by one term.[30]

It is known from earlier research that when using the unemployment rate to estimate the Phillips curve for Japan, the performance can be improved by using the reciprocal of the unemployment rate. I also found that forecasting performance was improved when the reciprocals of the flow data were used as independent variables. Therefore, in this paper, I shall report only those results obtained using the reciprocals in the case for the unemployment and the flow data.

The Phillips curve estimation results are presented in Tables 6 to 8.

A review of the results confirms that all variables used as independent variables have signs that are consistent with theoretical assumptions. Furthermore, all variables exhibit statistically significant values.[31]

However, it should be noted that when *WAGE* (total cash earnings) is used as an independent variable, overall performance deteriorates as compared to when CPI and the GDP deflator are used. As I pointed out earlier, this may be because wages continued to rise through the second half of the 1990s, when most macroeconomic indicators were following an uninterrupted downward trend. For CPI and the GDP deflator, I estimated *m*-tests to check for serial correlation in the error terms. My results do not uncover serial correlation in any of the estimations. Furthermore, because of the very small number of variables used in some of the estimation formulas, I performed Ramsey Tests (RESET verification) to check for errors in the specification of the model. The results of this test appear in the tables as *p*-values. The null hypothesis that the model contained specification errors was rejected at the 10 percent level only in the case where *WAGE* and *UGAP* were used as a dependent variable and an independent variable, respectively.

Next, I used these estimation formulas to undertake an out-of-sample forecast and chose the following variables for forecasting: CPI, GDP deflator, hourly total cash earnings, and trimmed-mean CPI.[32]

30. I also tested with the current term and several lags and obtained no significant change in forecasting performance. Therefore, in this paper I have only given the results of one lag for all variables.

31. Following the method of Bleakley *et al.* (1999), I also undertook estimations using the two flow variables, *ue* and *eu*, as explanatory variables. The results appear in the top right-hand column. When both flow variables are used simultaneously, estimation performance deteriorates when a constant term is used as compared to when it is not used. Therefore, the above tables show results for only when the constant term has been removed. Given the extremely strong correlation between the *ue* and *eu* flows observed in Table 5, perhaps estimation performance is being weakened by multicollinearity.

32. The trimmed-mean CPI is computed by eliminating all items undergoing large relative-price fluctuations. Mio (2001) used the trimmed-mean CPI to control supply shocks and estimated the Phillips curve. His results indicate that this approach yields better performance than the conventional approach of using import prices as supply shock. See Mio (2001) for details. I thank Hitoshi Mio (Bank of Japan) for providing me with his data for the analysis of this paper.

Table 6 Phillips Curve Estimation Results (Dependent Variable: *CPI*)

[1] Independent Variables: Flow Data

Const.	1.964 (2.908)***	−0.802 (−2.669)**	— (—)
$CPI_{(-1)}$	0.609 (4.638)***	0.606 (4.621)***	0.604 (4.608)***
$CPI_{(-2)}$	0.290 (2.015)**	0.308 (2.152)**	0.303 (2.114)**
$CPI_{(-3)}$	0.101 (0.662)	0.098 (0.643)	0.099 (0.653)
$CPI_{(-4)}$	−0.438 (−2.931)***	−0.444 (−2.977)***	−0.442 (−2.967)***
$CPI_{(-5)}$	0.223 (1.828)*	0.233 (1.926)*	0.229 (1.894)*
$1/ue_{(-1)}$	−23.761 (−2.870)***	— (—)	−7.026 (−2.691)***
$1/eu_{(-1)}$	— (—)	0.364 (2.906)***	0.263 (2.964)***
IMP	0.017 (3.258)***	0.016 (2.925)***	0.016 (3.024)***
R^2-adj.	0.866	0.866	0.883
D.W.	2.027	2.045	2.040
m-test	−0.315 [0.754]	−0.527 [0.601]	−0.467 [0.643]
RESET	1.455 [0.232]	1.170 [0.337]	1.248 [0.305]

[2] Independent Variables: Male and Female Flow Data

Const.	2.150 (2.307)**	1.289 (2.841)***	−0.966 (−2.431)**	−0.536 (−2.489)**
$CPI_{(-1)}$	0.639 (4.764)***	0.630 (4.872)***	0.603 (4.442)***	0.632 (4.918)***
$CPI_{(-2)}$	0.288 (1.945)*	0.299 (2.070)**	0.296 (2.032)**	0.323 (2.250)**
$CPI_{(-3)}$	0.100 (0.636)	0.089 (0.584)	0.082 (0.529)	0.105 (0.685)
$CPI_{(-4)}$	−0.436 (−2.836)***	−0.444 (−2.967)***	−0.460 (−3.042)***	−0.429 (−2.873)***
$CPI_{(-5)}$	0.207 (1.614)*	0.258 (2.138)**	0.221 (1.779)*	0.250 (2.076)**
$1/mue_{(-1)}$	−24.462 (−2.274)**	— (—)	— (—)	— (—)
$1/fue_{(-1)}$	— (—)	−16.710 (−2.799)***	— (—)	— (—)
$1/meu_{(-1)}$	— (—)	— (—)	0.417 (2.585)**	— (—)
$1/feu_{(-1)}$	— (—)	— (—)	— (—)	0.258 (2.880)***
IMP	0.016 (2.842)***	0.018 (3.472)***	0.012 (2.063)**	0.019 (3.571)***
R^2-adj.	0.858	0.865	0.862	0.866
D.W.	2.027	2.055	1.993	2.078
m-test	0.285 [0.777]	−0.562 [0.577]	−0.002 [0.996]	−0.718 [0.476]
RESET	1.572 [0.198]	1.212 [0.319]	1.047 [0.394]	1.287 [0.289]

[3] Independent Variables: Others

Const.	−0.838 (−2.276)**	0.357 (2.167)**	−0.751 (−3.046)***	0.842 (3.330)***	0.805 (2.601)**
$CPI_{(-1)}$	0.610 (4.474)***	0.641 (4.773)***	0.553 (4.197)***	0.590 (4.614)***	0.600 (4.402)***
$CPI_{(-2)}$	0.306 (2.086)**	0.300 (2.023)**	0.225 (1.582)	0.255 (1.802)*	0.279 (1.902)*
$CPI_{(-3)}$	0.081 (0.520)	0.067 (0.427)	0.039 (0.264)	0.031 (0.207)	0.048 (0.309)
$CPI_{(-4)}$	−0.458 (3.005)***	−0.452 (−2.943)***	−0.466 (−3.210)***	−0.414 (−2.832)***	−0.428 (−2.819)***
$CPI_{(-5)}$	0.207 (1.632)*	0.254 (2.045)**	0.291 (2.493)**	0.319 (2.716)***	0.296 (2.433)**
$1/u_{(-1)}$	2.985 (2.445)**	— (—)	— (—)	— (—)	— (—)
$ugap_{(-1)}$	— (—)	−0.504 (−2.229)**	— (—)	— (—)	— (—)
$yukou_{(-1)}$	— (—)	— (—)	1.245 (3.381)***	— (—)	— (—)
$gdpgap1_{(-1)}$	— (—)	— (—)	— (—)	0.156 (3.339)***	— (—)
$gdpgap2_{(-1)}$	— (—)	— (—)	— (—)	— (—)	0.111 (2.565)**
IMP	0.013 (2.227)**	0.012 (2.071)**	0.005 (0.768)	0.011 (2.036)**	0.012 (2.176)**
R^2-adj.	0.857	0.857	0.873	0.872	0.862
D.W.	1.965	1.965	1.984	2.144	2.047
m-test	0.067 [0.947]	0.298 [0.767]	0.006 [0.995]	−1.104 [0.275]	−0.476 [0.636]
RESET	1.428 [0.240]	1.400 [0.249]	1.531 [0.209]	0.928 [0.456]	0.899 [0.473]

Notes: 1. Figures in parentheses indicate *t*-values. ***, **, and *, respectively, indicate 1 percent, 5 percent, and 10 percent levels of significance. Figures in brackets indicate *p*-values.

2. Estimations using CPI or the GDP deflator as the dependent variable were tested for serial correlation of error terms, and *m*-test results are given in Tables 6 and 7.

Table 7 Phillips Curve Estimation Results (Dependent Variable: *GDPDEF*)

[1] Independent Variables: Flow Data

Const.	3.202 (3.841)***	–1.532 (–3.666)***	— (—)
$GDPDEF_{(-1)}$	0.591 (4.592)***	0.574 (4.328)***	0.571 (4.352)***
$GDPDEF_{(-2)}$	0.227 (1.500)	0.243 (1.602)	0.236 (1.566)
$GDPDEF_{(-3)}$	0.117 (0.783)	0.127 (0.842)	0.125 (0.835)
$GDPDEF_{(-4)}$	–0.294 (–2.554)**	–0.260 (–2.242)**	–0.271 (–2.359)**
$GDPDEF_{(-5)}$	— (—)	— (—)	— (—)
$1/ue_{(-1)}$	–41.496 (–3.850)***	— (—)	–13.926 (–3.799)***
$1/eu_{(-1)}$	— (—)	0.603 (3.714)***	0.423 (3.837)***
R^2-adj.	0.897	0.895	0.897
D.W.	1.842	1.806	1.814
m-test	0.138 [0.891]	0.407 [0.686]	0.339 [0.736]
RESET	1.006 [0.414]	0.777 [0.546]	0.900 [0.472]

[2] Independent Variables: Male and Female Flow Data

Const.	3.135 (3.172)***	1.775 (3.076)***	–1.383 (–2.949)***	–0.907 (–3.170)***
$GDPDEF_{(-1)}$	0.668 (5.229)***	0.642 (4.870)***	0.620 (4.530)***	0.655 (5.110)***
$GDPDEF_{(-2)}$	0.237 (1.509)	0.247 (1.574)	0.229 (1.443)	0.279 (1.799)*
$GDPDEF_{(-3)}$	0.115 (0.743)	0.105 (0.675)	0.125 (0.799)	0.109 (0.707)
$GDPDEF_{(-4)}$	–0.301 (–2.507)**	–0.271 (–2.263)**	–0.250 (–2.072)**	–0.275 (–2.316)**
$GDPDEF_{(-5)}$	— (—)	— (—)	— (—)	— (—)
$1/mue_{(-1)}$	–37.933 (–3.178)***	— (—)	— (—)	— (—)
$1/fue_{(-1)}$	— (—)	–25.008 (–3.094)***	— (—)	— (—)
$1/meu_{(-1)}$	— (—)	— (—)	0.511 (2.983)***	— (—)
$1/feu_{(-1)}$	— (—)	— (—)	— (—)	0.384 (3.264)***
R^2-adj.	0.889	0.888	0.897	0.899
D.W.	1.848	1.816	1.767	1.832
m-test	0.098 [0.922]	0.513 [0.610]	0.750 [0.457]	0.638 [0.526]
RESET	0.927 [0.456]	0.437 [0.781]	0.281 [0.889]	1.018 [0.408]

[3] Independent Variables: Others

Const.	–1.508 (–3.360)***	0.338 (2.773)***	–0.808 (–3.672)***	0.712 (3.313)***	1.113 (4.573)***
$GDPDEF_{(-1)}$	0.589 (4.358)***	0.615 (4.617)***	0.757 (10.982)***	0.577 (4.215)***	0.504 (3.921)***
$GDPDEF_{(-2)}$	0.255 (1.652)	0.266 (1.711)*	— (—)	0.224 (1.840)*	0.219 (1.953)*
$GDPDEF_{(-3)}$	0.108 (0.707)	0.124 (0.800)	— (—)	— (—)	— (—)
$GDPDEF_{(-4)}$	–0.278 (–2.358)**	–0.240 (–2.018)**	— (—)	— (—)	— (—)
$GDPDEF_{(-5)}$	— (—)	— (—)	— (—)	— (—)	— (—)
$1/u_{(-1)}$	4.527 (3.401)***	— (—)	— (—)	— (—)	— (—)
$ugap_{(-1)}$	— (—)	–0.727 (–3.280)***	— (—)	— (—)	(—)
$yukou_{(-1)}$	— (—)	— (—)	1.032 (3.691)***	— (—)	— (—)
$gdpgap1_{(-1)}$	— (—)	— (—)	— (—)	0.163 (3.679)***	— (—)
$gdpgap2_{(-1)}$	— (—)	— (—)	— (—)	— (—)	0.186 (4.899)***
R^2-adj.	0.891	0.890	0.888	0.888	0.903
D.W.	1.762	1.777	2.160	2.040	1.906
m-test	0.752 [0.455]	0.755 [0.454]	–0.879 [0.383]	–1.631 [0.109]	–0.557 [0.580]
RESET	0.459 [0.765]	0.707 [0.591]	0.781 [0.543]	0.427 [0.788]	0.589 [0.672]

Notes: 1. Figures in parentheses indicate *t*-values. ***, **, and *, respectively, indicate 1 percent, 5 percent, and 10 percent levels of significance. Figures in brackets indicate *p*-values.
2. Estimations using CPI or the GDP deflator as the dependent variable were tested for serial correlation of error terms, and *m*-test results are given in Tables 6 and 7.

Table 8 Phillips Curve Estimation Results (Dependent Variable: *WAGE*)

[1] Independent Variables: Flow Data

Const.	13.196 (5.523)***	–4.033 (–4.058)***	— (—)
$CPI_{(-1)}$	0.600 (0.815)	0.375 (0.532)	0.406 (0.572)
$CPI_{(-2)}$	0.019 (0.017)	0.059 (0.056)	0.057 (0.053)
$CPI_{(-3)}$	1.271 (1.136)	1.345 (1.266)	1.329 (1.242)
$CPI_{(-4)}$	–1.553 (–2.265)**	–1.363 (–2.099)**	–1.414 (–2.163)**
$1/ue_{(-1)}$	–144.231 (–4.949)***	— (—)	–34.311 (–3.941)***
$1/eu_{(-1)}$	— (—)	2.383 (5.712)***	1.847 (6.166)***
R^2-adj.	0.649	0.683	0.678
D.W.	1.877	1.881	1.892
RESET	0.322 [0.862]	0.314 [0.867]	0.333 [0.853]

[2] Independent Variables: Male and Female Flow Data

Const.	18.330 (5.893)***	7.601 (4.474)***	–5.910 (–4.656)***	–1.669 (–2.251)**
$CPI_{(-1)}$	0.397 (0.551)	1.077 (1.387)	–0.129 (–0.177)	1.064 (1.457)
$CPI_{(-2)}$	0.339 (0.310)	–0.238 (–0.197)	0.092 (0.087)	–0.072 (–0.063)
$CPI_{(-3)}$	1.214 (1.122)	1.294 (1.070)	1.263 (1.205)	1.382 (1.204)
$CPI_{(-4)}$	–1.824 (–2.728)***	–1.336 (–1.806)*	–1.320 (–2.061)**	–1.392 (–1.982)*
$1/mue_{(-1)}$	–194.830 (–5.447)***	— (—)	— (—)	— (—)
$1/fue_{(-1)}$	— (—)	–81.675 (–3.678)***	— (—)	— (—)
$1/meu_{(-1)}$	— (—)	— (—)	3.061 (5.918)***	— (—)
$1/feu_{(-1)}$	— (—)	— (—)	— (—)	1.415 (4.540)***
R^2-adj.	0.671	0.589	0.692	0.630
D.W.	2.057	1.625	1.863	1.707
RESET	0.202 [0.936]	0.289 [0.884]	0.523 [0.719]	0.504 [0.733]

[3] Independent Variables: Others

Const.	–5.309 (–4.485)***	4.582 (20.349)***	–2.374 (–4.766)***	5.670 (7.511)***	7.824 (17.056)***
$CPI_{(-1)}$	–0.058 (–0.080)	— (—)	— (—)	0.588 (2.333)**	— (—)
$CPI_{(-2)}$	0.141 (0.133)	— (—)	— (—)	— (—)	— (—)
$CPI_{(-3)}$	1.309 (1.244)	— (—)	— (—)	— (—)	— (—)
$CPI_{(-4)}$	–1.550 (–2.403)**	— (—)	— (—)	— (—)	— (—)
$1/u_{(-1)}$	23.076 (5.848)***	— (—)	— (—)	— (—)	— (—)
$ugap_{(-1)}$	— (—)	–4.864 (–11.476)***	— (—)	— (—)	— (—)
$yukou_{(-1)}$	— (—)	— (—)	6.141 (11.153)***	— (—)	— (—)
$gdpgap1_{(-1)}$	— (—)	— (—)	— (—)	0.804 (6.156)***	— (—)
$gdpgap2_{(-1)}$	— (—)	— (—)	— (—)	— (—)	0.886 (11.631)***
R^2-adj.	0.689	0.700	0.688	0.695	0.706
D.W.	1.936	1.923	1.765	2.195	1.787
RESET	0.172 [0.952]	2.558 [0.050]**	2.052 [0.101]	1.197 [0.324]	0.664 [0.620]

Note: Figures in parentheses indicate t-values. ***, **, and *, respectively, indicate 1 percent, 5 percent, and 10 percent levels of significance. Figures in brackets indicate p-values.

I adopted the following three forecast periods:

(1) 1997/I–2000/I; using the coefficients estimated over 1986/I–1996/IV.
(2) 1998/I–2000/I; using the coefficients estimated over 1986/I–1997/IV.
(3) 1999/I–2000/I; using the coefficients estimated over 1986/I–1998/IV.

Actual values were used for variables during the estimation period, and a dynamic forecast was undertaken for the inflation lag term during the forecasting period. Actual values were also used for the flow data and other independent variables during the forecasting period.

In Table 9, the error between forecasted and actual values is compared using the root mean squared error (RMSE). The independent variables used are named in the second row of the table. RMSE using flow data appear in the left-hand portion of the table, while RMSE using other variables appear in the right-hand portion. The first difference of unemployment rate (Δu) as a dependent variable is also estimated in Table 9. Δu can be considered as the net amount of all the flow data. In addition, Δu can be considered a variable that captures the speed limit effect.

In all instances, forecasting performances for *CPI*, *trimmed-mean CPI*, and *GDPDEF* were improved by using flow data instead of the unemployment rate (*u*). Moreover, flow data outperformed the gap between the equilibrium unemployment rate and the unemployment rate (*ugap*), the first difference of the unemployment rate (Δu), and the output gap (*gdpgap1*, *gdpgap2*). In particular, the *ue* flow generally performed well in forecasting *CPI* and *GDPDEF*. Likewise, cases using the flows of women (*fue*) performed well in forecasting *CPI*. However, the results also show that, in forecasting *trimmed-mean CPI*, predictive performance can be improved by using *feu* flows instead of *fue* flows, depending on the forecast period.

Table 9 RMSE Results

	Flow data							Other variables					
	1/*ue*	1/*mue*	1/*fue*	1/*eu*	1/*meu*	1/*feu*	1/*ue*, 1/*eu*	1/*u*	*ugap*	Δu	*yukou*	*gdpgap1*	*gdpgap2*
CPI													
1997/I–2000/I	0.5980	0.7694	0.3116	0.9461	0.8672	0.7770	0.8381	0.8614	1.0059	0.3821	0.3247	0.6646	0.5636
1998/I–2000/I	0.6056	0.7139	0.3471	0.7177	0.7623	0.5697	0.7014	0.7279	1.1054	0.4474	0.3593	0.6679	0.6632
1999/I–2000/I	0.2344	0.2344	0.1842	0.2135	0.2295	0.2114	0.2272	0.1972	0.3678	0.6525	0.3426	0.2109	0.2330
Trimmed-mean CPI													
1997/I–2000/I	0.1883	0.2655	0.3782	0.5238	0.5083	0.1517	0.3460	0.4998	0.5498	0.5407	0.1840	0.3786	0.4275
1998/I–2000/I	0.3092	0.3234	0.4964	0.3327	0.4615	0.2785	0.3072	0.3917	0.7172	0.3836	0.1911	0.4535	0.4733
1999/I–2000/I	0.1987	0.2668	0.0328	0.3316	0.5007	0.0884	0.2979	0.3791	0.7662	0.1143	0.0488	0.4789	0.5346
GDPDEF													
1997/I–2000/I	0.2082	0.4855	0.5109	0.7042	0.3792	0.5235	0.5198	0.5327	0.8002	0.6412	0.3883	0.4171	0.5456
1998/I–2000/I	0.2367	0.4007	0.5044	0.5118	0.3708	0.3456	0.4337	0.4932	0.9987	0.7723	0.4041	0.4274	0.7472
1999/I–2000/I	0.3492	0.5211	0.6565	0.3541	0.4311	0.7295	0.3203	0.3628	0.2601	1.5714	0.7281	0.3684	0.1863
WAGE													
1997/I–2000/I	1.4729	1.2925	1.7840	1.5465	1.7262	1.5558	1.4681	1.7067	1.9609	1.7011	1.6965	1.5817	1.2033
1998/I–2000/I	1.4580	1.0840	1.9255	1.1128	0.8516	1.6262	1.1717	0.8264	1.6410	1.7606	1.7653	1.2380	1.0125
1999/I–2000/I	0.5163	0.6083	0.9911	0.2923	0.7501	0.8795	0.3106	0.4081	2.2861	1.6239	1.1829	0.5733	0.7915

Note: Shadowed figures indicate minimum RMSE values.

Among variables other than flow data, the results show that cases using the effective ratio of job offers to applicants (*yukou*) perform as well as cases using flow data. As the effective ratio of job offers to applicants is reported by public employment security offices, this data series has been criticized for its low level of coverage of job seekers and job openings. Nevertheless, my results underscore the possibility of improving inflation forecasting by using variables that directly reflect the dynamics of the labor market, such as the flow data and the effective ratio of job offers to applicants. The convenience of flow data and the effective ratio of job offers to applicants should also be taken into account as, unlike GDP data, they are available as monthly statistics. It should be noted however, that the flow variables which provide the best forecast differ among the independent variables.

Regarding the forecasting of *WAGE*, the use of flow data and effective ratio of job offers to applicants as well as all other independent variables did not improve forecasting performance. As mentioned above, the significant gap between actual figures and forecasts based on estimations using previous actual figures may be attributed to the downward rigidity in nominal wages in the second half of the 1990s. If in fact the conclusion that the rising unemployment rate in the second half of the 1990s was caused by downward rigidity in nominal wages[33] is correct, then it will be necessary to determine which flows were pushed upward and which were pushed downward, resulting in higher unemployment rates. This question, as well as the verification of whether wages were in fact downwardly rigid in the second half of the 1990s, are subjects for future research.

V. Conclusion

Using the flow data between the three states of employment, unemployment, and not-in-the-labor-force, I have undertaken a detailed examination of factors contributing to changes in Japan's unemployment rate.

The results of the analysis provide the following explanations for Japan's rising unemployment rate after the collapse of the bubble economy. First, the transition probability from employment to unemployment has risen, and at the same time, the transition rate from unemployment to employment has declined significantly. Second, the transition probability from unemployment to not-in-the-labor-force has declined for both men and women, resulting in the accumulation of unemployment. Third, the results point to the possibility that the unemployment rate was also pushed up by the flow of workers from not-in-the-labor-force to unemployment. Parallel to a decline in the transition probability from not-in-the-labor-force to employment, an increased inflow of men from not-in-the-labor-force to unemployment began in the mid 1990s. The same trend is observable for women beginning between the end of the 1990s and 2000.

Next, I turned to the question of whether the performance of the Phillips curve in forecasting price movements could be improved by using flow data instead of the

33. See, for example, Ohtake (2001).

unemployment rate, which is an accumulation of the various types of movements of workers. The results indicate that the forecasting performance of the Phillips curve can in fact be improved by using flow data for movements between employment and unemployment that are sensitive to trends in price levels and business conditions. Furthermore, the results showed that forecasting performance when flow data are used was at least as good as cases in which other variables were used, such as the gap between the unemployment rate and the equilibrium unemployment rate, and output gap.

On the other hand, no clear conclusions could be obtained on the existence of an added worker effect or discouraged worker effect. This was primarily due to data limitations. Numbers of samples were limited throughout, and some flow data were only partially available for certain periods of time. The question of how these two effects and various worker flows influence changes in the equilibrium unemployment rate (natural unemployment rate), which is an important indicator in policy decisions, requires additional research using detailed structural models.

Japan is currently experiencing a growing diversity of work formats, and the introduction of work-sharing arrangements is under consideration.[34] Under such conditions, it is conceivable that flows of workers between the three states of employment, unemployment, and not-in-the-labor-force will differ significantly from previous patterns. In view of the likelihood that trends in business conditions and developments in the labor market will become even more closely related to each other in the future, it will be necessary to use flow-data analysis in examining various questions, including the issues that have been identified above for future study.

34. With the growing number of workers in a wide variety of nonstandard staffing arrangements, it is possible that the probability of finding employment may improve among part-timers and agency temporaries whose hourly wages make them less expensive than full-time employees. In that case, it will be necessary to consider the possibility that the relation between prices and wages and *ue* flow obtained from historical data will change (the possibility that the coefficients of flow variables may become smaller).

APPENDIX: STEADY-STATE UNEMPLOYMENT RATE

The computations summarized in Tables 3 and 4 were generated under the assumption that the transitions among the three labor force states are governed by a Markov process. The Markov process consists of a stochastic process whereby the state at time $t + 1$ depends solely on the state at t.

The nine transition probabilities shown in Table 2 are expressed as a 3×3 transition matrix. Using this transition matrix, E, U, and N at each point in time can be expressed as shown in equation (A.1) below.

$$\begin{pmatrix} E_{t+1} \\ U_{t+1} \\ N_{t+1} \end{pmatrix} = \begin{pmatrix} ee & ue & ne \\ eu & uu & nu \\ en & un & nn \end{pmatrix} \begin{pmatrix} E_t \\ U_t \\ N_t \end{pmatrix}. \tag{A.1}$$

Based on the nine transition probabilities, this transition matrix depicts the movement of people in and out of the three states of employment, unemployment, and not-in-the-labor-force between time t and $t + 1$. For purposes of simplification, this transition matrix can be rewritten as follows.

$$X(t+1) = P(t)X(t). \tag{A.2}$$

At time = 0, equation (A.2) implies the following:

$$\begin{aligned} X(1) &= P(0)X(0) \\ X(2) &= P(1)X(1) \\ X(3) &= P(2)X(2) \\ &\vdots \end{aligned} \tag{A.3}$$

Assuming that the conditions of the transition matrix remain unchanged over time ($P(0) = P(1) = \cdots = P(m) = P$), equation (A.2) becomes

$$X(m+1) = P^m X(0). \tag{A.4}$$

If the Markov chain P is ergodic, P^m converges on a probability matrix A when $m \rightarrow \infty$. At such time, the following relation holds for a random probability vector π:

$$\lim_{m \to \infty} \pi P^m = \pi A = \omega, \tag{A.5}$$

where ω denotes the unique probability vector (eigenvector) that satisfies $\xi P = \xi$.[35]

The computations of Tables 3 and 4 are based on the following assumptions. First, assuming that probabilities remain constant over time ($m \rightarrow \infty$), the transition matrix comprised of the nine transition probabilities for the years 1985, 1990, 1995, and 2000 converges on the probability matrix A. Having obtained A, the probability vector ω that satisfies $\xi P = \xi$ can be computed. This is assumed to represent E, U, and N in the steady state (steady-state unemployment rate: $U/E + U$). For prior research using this method, see Kuhn and Schuetze (2001).

35. Here, ω is the normalized random vector the sum of whose elements is one, and it is a unique vector in that sense.

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