

The Dynamics of Worker Reallocation Within and Across Industries *

Amos Golan
American University

Julia Lane
The Urban Institute

Erika McEntarfer
Census Bureau

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Abstract

This paper uses an integrated employer-employee data set to answer two key questions:

1. What is the “equilibrium” amount of worker reallocation in the economy – both within and across industries?
2. How much does firm-level job reallocation affect the separation probabilities of workers?

Consistent with other work, we find that there is a great deal of reallocation in the economy, although this varies substantially across demographic group. Much worker reallocation is within the economy, roughly evenly split between within and across broadly defined industries. An important new finding is that much of this reallocation is confined to a relatively small subset of workers that is shuffled across jobs – both within and across industries – in the economy. However, we also find that even for the most stable group of workers, firm level job reallocation substantially increases the probability of transition for even the most stable group of workers. Finally, workers who are employed in industries that provide low returns to tenure are much more likely to reallocate both within and across industries.

Keywords: Matched employer-employee data; worker reallocation; job reallocation

JEL codes: J63, J21; J23

I. Introduction

The dynamism of the U.S. economy is one of its most striking characteristics, and one of the reasons for its success. This dynamism is clear in many areas: the flows of venture capital to promising firms; the enormous reallocation of jobs from less productive to more productive firms; the even larger flows of workers from one firm, industry, or geographic area to another. Although the levels and fluctuations of worker flows have been well documented, little is known about the degree of within and across industry worker reallocation. This paper uses a new data source to fill the gap.

An empirical study of workers' transitions within and across industries has been difficult due to the lack of suitable data. Previously available data, which are either worker-based or firm-based, do not permit a full analysis of the dynamic interaction between workers and firms. In the former case, the sample size of worker-based data sets is not large enough to accurately measure transitions for detailed demographic groups within and across detailed industries – and the ability of workers to accurately identify their employers' detailed industry is questionable. In the latter case, some firm based datasets can describe job reallocation, but not worker reallocation.

In this paper, we use a large new dataset that captures the interrelationship between employers and employees – and the reallocation of workers within and across industries. This permits us, for the first time, to estimate the equilibrium transitions of workers (modeled as a stationary Markov process) at the detailed industry level, as well as the relationship between firm-level reallocation and the likelihood of worker separation.

Consistent with other work, we find that there is a great deal of reallocation in the economy, although this varies substantially across demographic group. Much worker reallocation is within the economy, roughly evenly split between within and across broadly defined industries. An important new finding is that much of this reallocation is confined to a relatively small subset of workers that is shuffled across jobs – both within and across industries – in the economy. However, firm level job and worker reallocation still substantially increases the probability of transition for even the most stable group of workers, even after controlling for individual characteristics and firm and industry tenure. Finally, workers who are employed in industries that provide low returns to tenure are much more likely to reallocate both within and across industries.

In the next section we provide some background discussion on workers' job reallocations. In Section 3 we discuss the basic economic and econometrics background for the empirical analysis. In Section 4 we briefly discuss the basic data and data construction. In Section 5 we discuss the estimated transitions for the whole population and by demographic groups. We also show here the transitions across and within industries. In Section 6 we analyze the worker-firm level job reallocation and workers' separations. We conclude in Section 7. The Appendix describes our estimation approach.

2. Worker and Job reallocation - Background

There are enormous amounts of both job and worker reallocation in the US. Armington et al. (1998) estimate that the annual job reallocation rate is about 30% of the working force, while Anderson and Meyer (1994) and Burgess et al. (2000) estimate that the quarterly worker reallocation rate exceeds 40%¹. Reallocation varies by (i) industry where turnover is higher in retail trade and lower in manufacturing, and by (ii) type of worker where turnover is much higher for young than for old workers, for high school educated workers than for college graduates, and for women than for men (Lane, 2000).

Why do these high rates of job and worker reallocation occur? One reason for job reallocation is that technological change and demand shifts enhance the reallocation of production, and the associated jobs, from declining to expanding industries. Quantifying the amount of across industry allocation is critical to understanding this process². Similarly, the process of “creative destruction” means that less productive firms will shrink and die and hence destroy jobs, while the more productive firms will expand and be born and create jobs. Thus, jobs will get reallocated even within quite narrowly defined industries (Foster et al. 2001). Quantifying the amount of within industry reallocation is critical to understanding this.

Worker reallocation over and above job reallocation can occur because workers change jobs simply to improve their current lot (Farber, 1999) or future lot (Mincer and Polachek, 1974). In addition, workers reallocate in response to changing demographic forces, such as workforce aging, childbearing, and education acquisition. Finally, some worker reallocation occurs as workers and firms sort to find their “best” matches. Since much of this reallocation is likely to be driven by demographic characteristics, it is important to quantify the degree of within and across industry reallocation by demographic group.

There are other, more wide-ranging reasons to be interested in this reallocation process. One reason is that to the extent that such reallocation reflects frictions in the labor market, it directly affects the unemployment rate (see Petrongolo and Pissarides, 2001 for a good survey). Indeed, work by Blanchard and Diamond (1989) examining the transitions into and out of the labor force and employment, using the gross flows statistics from the Current Population Survey, shows that the unemployment rate is heavily affected by such flows. However, empirical estimates of this relationship that ignore employer-to-employer transitions will be substantially biased. Recent work by Fallick

¹ Job reallocation is here defined as the sum of job creation (jobs added by new and expanding establishments) and job destruction (jobs lost by exiting and contracting establishments). Worker reallocation is measured as the average of accessions and separations at the establishment level. Rates are derived by dividing counts by the average of employment in the reference and previous periods.

² Note that the reallocation that is being described here is separate from cyclical variations in employment reallocation.

and Fleischmann (2004) suggests that such job-to-job flows are important since just as many workers move from one employer to another as those who move into and out of employment.

Another reason to be interested in such flows is that they are important in evaluating the inter-relationship between policy changes, macro-economic conditions and the employment flow and structure. Because there are substantial differences in reallocation by demographic groups, changes in policy, such as the 1996 welfare reform, which bring many younger, unskilled workers into the workforce, are likely to have substantial impacts on the amount of labor market friction. Topel and Ward (1992) have pointed out that young workers in the labor market experience a large number of relatively short-spell jobs.

Finally, the burden of worker reallocation can be quite substantial for the affected workers. For example, the dual labor market literature suggests that shocks to product demand are borne by a buffer, secondary, labor market, comprised primarily of less educated, less tenured and minority workers, who are easier to shed and rehire than workers in the primary labor market (Dickens and Lang, 1985).

What does this study contribute to the literature? The order of magnitude of worker flows into and out of employment, and into and out of jobs is reasonably well quantified (Fallick and Fleischman, 2004), as are the characteristics of workers hired into expanding industries rather than slow-growing industries (Fallick, 1996). But previous attempts to quantify the core amount of transitions across detailed industries for detailed demographic groups have been hampered by data limitations, since the main data-source for addressing this issue – the Current Population Survey - is limited by heterogeneity, matching issues, and other sources of bias (Fallick and Fleischmann, 2004), as well as sample size constraints. Furthermore, the analysis has only been possible for year to year transitions, rather than over a long period of time, which permits an examination of the persistence of within and across industry reallocation.

In this study, we use a longitudinal matched employer-employee data with millions of observations over a nine year period, to quantify the order of magnitude of worker reallocation. Specifically, we study across and within industry job reallocation, and the reallocation of workers by demographic group and experience. This study provides empirical answers to the following questions:

1. What is the “equilibrium” amount of worker reallocation in the economy – both within and across industries as well as by different demographic groups?
2. How much does firm-level job reallocation affect the separation probabilities of workers?

3. Empirical Approach

The first task is to empirically quantify the structure of worker reallocation from job to job, industry to industry, and into and out of the workforce. We model that structure as a first order Markov transition probability matrix which is consistent with the belief that the labor market has a “short” term memory, yet current behavior depends on the previous period. We estimate the matrix for the economy as a whole as well as for the major demographic groups (gender and age levels), while conditioning on macroeconomic effects.

The five mutually exclusive states of nature that fully characterize the different basic states of firm and industry attachment for each worker are:

1. Employed with the same employer at time t and $t-1$ (Stayer).
2. Employed by a different employer between time t and $t-1$, but within the same industry (Firm, but not industry, Switcher).
3. Employed by a different employer and different industry between time t and $t-1$ (Industry Switcher).
4. Employed at time $t-1$ but not employed at time t (Exiter).
5. Not employed at time $t-1$ but employed at time t (Entrant).

Each of these states is defined on two consecutive periods. Though, it is somewhat different than the traditional way, these states seem to be a natural way of defining the labor market we analyze. We use these states throughout our analysis. Even though our data capture almost the whole universe of workers for the economies analyzed, there are a number of economic and econometric issues that have to be considered in the estimation procedure. First, we wish to estimate the steady state (equilibrium) transition matrix based on the available noisy panel data. Second, we wish to perform this estimation with minimal statistical assumptions while incorporating all the available information. Third, since we are uncertain about the exact functional forms and relationships among the different explanatory variables, we need to find a way to capture this information directly from the empirical moments.

This means that in order to provide us with the equilibrium (or steady-state) transition estimates, our estimation model must accommodate for possible small random changes in the yearly transitions. Second, our model must take into account the direct and indirect impact of global variables, such as global macro indicators or regional policies, on the estimated probabilities. Third, as with all data, the observed data are noisy – there are transcription and processing errors that occur in a non-systematic fashion. In particular, work by Abowd and Vilhuber (2004) finds that job flows are overstated by about 4% a quarter; worker flows by as much as 10%. Similarly, firm entry and exit may be overstated by as much as 10% (Benedetto et al., 2005). The model must take this into consideration. Fourth, since the underlying process generating these data is unknown, we do not want to impose any distributional structure or assumptions that may distort our estimates.

There are numerous methods that allow us to estimate the transition matrix, most of which fall within the class of maximum likelihood estimators for estimating discrete choice type models. Other possibilities include just analyzing the sample moments and averaging over the period analyzed to get a single transition matrix. But these methods are not attractive if one wishes to accommodate for the issues discussed above. Specifically, with the natural states defined above, and if we wish to accommodate for all of the above four major issues, and do it with minimal assumptions, we need to resort to a more generalized estimation framework. The method we use here is a member of the class of Information Theoretic (IT) estimation methods. This method, called Generalized Cross Entropy (GCE), is semi-parametric and allows us to accommodate for the basic four requirements described earlier. First, rather than use zero-moment conditions, we use stochastic moments, meaning we accommodate for possible noise in the data but without forcing the observed moments to be noisy. Second, rather than choosing an exact underlying likelihood, we do not start by choosing a likelihood function, but use a more flexible form of likelihood. Third, to accommodate for all the information we have in the data, but without specifying an exact functional form, we introduce this information (macro-level covariates) via their moment interaction with our panel data. Finally, the method we use (see details in Appendix) has the same level of complexity as the traditional Maximum Likelihood (ML), includes the ML as a special case where the observed data (moments) are perfect and noiseless and allows us to incorporate prior information. Since that method is not more complex than the ML (it has the same number of basic parameters), it uses less statistical assumptions and it is more stable (lower variances), it seems like a natural choice for analyzing the data we have.

In general, the Markov model falls within the class of discrete-choice models. For that class of models, the GCE is a generalized ML-Logit method that includes the ML-Logit as a special case but it is statistically and computationally more efficient for any finite sample. A detailed formulation and discussion of the GCE is provided in the appendix, and good background information is also found in Golan, Judge and Miller (1996), Golan, Judge and Perloff (1996) and the recent special issue of the *Journal of Econometrics* (2002).

The second task is to estimate the effect of firm-level job reallocation on the probability of worker separation, controlling for demographic variables. To accomplish this task, we use the traditional ML-Logit model to estimate the worker's probability of transitioning into the different states of nature for different demographic groups conditional on the job reallocation and churning rates of the firms for which they work. We use a firm fixed effect³ to capture the return to firm specific capital. In order to capture the effect of the returns to industry specific capital, we use an indicator variable that measures whether there are high returns to tenure in the industry¹.

4. Data and Definitions

The dataset used is drawn from the Longitudinal Employer-Household Dynamics (LEHD) Program at the US Census Bureau that permits us to describe the interactions

³ These issues are discussed in more detail in the following data section.

between workers and firms over time. This new database enables us to match workers with past and present employers, together with employer and worker characteristics. This database consists of quarterly establishment records of the employment and earnings of almost all individuals who worked in twenty-two U.S. states during the 1990's⁴. For the purposes of this paper, we work with data from the states of California, North Carolina, Illinois, Maryland and Florida from 1991 - 2001. All results presented are based on the pooled data from these individual states. In addition to the demographic groups discussed earlier, we use three macro-level variables to reflect the state of the economy during the period analyzed. These variables are the real interest rate, the growth rate of GDP and the unemployment rate.

These type of data have been extensively described elsewhere (Haltiwanger, Lane and Spletzer, 2000), but it is worth noting that there are several advantages for these data over household based, survey data. Most importantly for this research, we are able to accurately identify the industry for which people work, even at the three and four digit level of disaggregation⁵. The dataset is extremely large: even when we subset to individuals who work at least two quarters a year (as discussed below), there are between about 2.5 and three million individuals in the dataset every year. Over the 11 years for which we have data, there are more than 41,300,000 observations. There are other advantages: since we have almost the full universe of employers and workers, we can track movements across earnings categories and across employers with a great deal of accuracy. In addition, we can construct a long time series of transitions based on the micro-data – which cannot be constructed from any other dataset. Finally, although the unemployment insurance records themselves have no demographic information, the staff at the LEHD program has matched to internal administrative records that have information on date of birth, place of birth, race and sex for all workers, thus providing limited demographic information.

LEHD staff has also created measures of firm and individual fixed effects for each individual worker and firm in the dataset, estimated using recently developed econometric techniques (see Abowd et al. (2003)). The first of these measures, the firm fixed effect, is a summary measure of the wage premium (or discount) that each firm pays to observationally equivalent workers. This wage premium can reflect a variety of different factors such as the degree of unionization at a firm, the organizational structure, the degree of rent-sharing, or the capital intensity. The second, the individual fixed effect, is a summary measure of the pay premium (or discount) that is embodied in an individual as the individual moves across firms. Hence, it is a measure of the returns to non time varying individual characteristics – such as education, problem-solving skills, family background and the like. These are estimated over the period up to 1998, and are explicitly used in the probability model in the penultimate section of this paper.

⁴ The coverage of the ES202 and UI wage record data differs from the standard Census Bureau coverage: see Stevens (2001) and Abowd et al.(2004) for succinct descriptions of the differences.

⁵ Research using LEHD microdata suggest that respondent selfreports are not accurate indicators of industry and firm size classifications: see Andersson, Bolvig and Lane, 2005.

There are disadvantages as well. Most notably, there is no information on hours or weeks worked. In addition, when workers are not in the dataset, we do not know whether they are unemployed, out of the labor force, in school, or have left the state. There is also no information about occupation, so it is important to recognize that the transitions of workers from one industry to another may not reflect changes in the work that workers actually do.

A number of decisions need to be made in creating an analytical dataset. These job-based data are different from the worker-based data, with which many researchers are familiar, in that the unit of observation is a worker-firm match, and the data are longitudinal in both firms and workers. Earlier work with these types of data (Burgess et al. 2000) revealed that many job spells are extremely short. About 25% of job spells last less than a quarter, while most jobs are of long duration. In addition, about 90% of workers have only one employer. In order to focus on attached rather than peripheral workers, we convert the file to an annual file. We do so by calculating the total earnings for each employer-worker match within each year, keep in the data the subset of workers aged 18-65 who work at least two quarters during each year, and use as their employer the “dominant” employer for each worker (that employer from which the worker earned the most earnings).

5. Transitions

We begin by estimating the transition matrix for each one of the five states: California, North Carolina, Illinois, Maryland and Florida from 1991 – 2001. This initial analysis reveals that the basic transitions are practically (statistically) the same for each one of these states. Therefore, we pool the data and present only the economy-wide estimates here.

5.1 *Basic Statistics*

The transitions across the states of nature are calculated for the entire data sets and the results presented in Table 1. An examination of these statistics suggests that, in any given year, there is a great deal of stability among workers. Of the five basic states in the workforce, by far the most common state is the group who stay with one employer from one year to the next – they comprise about 56% of the dataset. About 21% of workers switch jobs every year – about half of these jobs switchers (11%) stay in the same major industry division⁶, and one half (10%) switch out of it. The dynamics vary quite substantially by demographic group: about 67% of older, male workers stay with their employer from one year to the next, compared with only 35% of younger male workers.

⁶ The major industry divisions are agriculture, mining, contract construction, manufacturing, wholesale trade, retail trade, finance, insurance and real estate (FIRE), services, and public administration. The industrial classifications used in the paper are the Standard Industrial Classifications (SIC).

Table 1: Calculated Labor Market Transitions Between Years
(Attached workers in CA, FL, IL, NC and MD, 18-65 years old)

Demographic Characteristics		Entrant	Job Switchers;		Stayer	Exiter	Counts
			Major Industry Switcher	Major Industry Stayer			
Sex	Age category in t						
Female	Young (18-25)	16.62%	19%	16%	36%	13%	2,064,067
	Middle-Age (26-55)	10.39%	8%	11%	60%	10%	8,043,380
	Older (over 55)	7.62%	4%	7%	68%	13%	956,813
Male	Young (18-25)	17.33%	21%	13%	35%	13%	2,183,834
	Middle-Age (26-55)	10.25%	9%	10%	60%	10%	9,179,478
	Older (over 55)	7.99%	5%	7%	67%	13%	1,099,559
All		11.30%	10%	11%	56%	11%	23,527,131

All person years, persons who have a dominant employer in t or t-1.

One obvious question that emerges from these basic statistics is whether workers classified as entrants to an industry were employed in the industry within the previous four years. The longitudinal nature of the data permits us to examine this. We present those results in Table 2, which makes it clear that the overwhelming majority of entrants, regardless of age or sex, are new to their industry. Indeed, fewer than one in five workers return to their major industry, while only about one in twenty of younger workers return to their detailed four digit industry, and only about one in ten older workers.

Table 2: Percentage of Entrants in 1996-2000 returning to an industry in which they were previously employed within the last four years.

Demographic Characteristics		Major Industry	Two-Digit SIC	Three-Digit SIC	Four-Digit SIC	Counts
Sex	Age category in 1996					
Female	Young (18-25)	12%	6%	5%	5%	217,669
	Middle-Age (26-55)	16%	11%	9%	8%	537,634
	Older (over 55)	18%	14%	12%	11%	47,832
Male	Young (18-25)	11%	6%	5%	4%	237,176
	Middle-Age (26-55)	17%	12%	10%	9%	601,899
	Older (over 55)	18%	14%	13%	12%	57,527
All		15%	10%	8%	8%	1,699,737

5.2 The “Equilibrium” Amount of Reallocation

Tables 1 and 2 represented a simple calculation of gross flows. However, for the reasons discussed in Section 3, these do not represent “equilibrium” reallocation rates.

We therefore applied the GCE estimation procedure and present the results in Table 3⁷. The first thing to note is the marked stability in employment among this group of attached workers in the analytical dataset. If we examine the first column, 74% of workers who have been with the same employer for at least two years (the first row) remain with that employer in the subsequent year. When we turn to examining workers who are less attached - workers who switched employers or industries in the previous year, only 50% stayed with the same employer in the subsequent period, and fewer than half (42%) of entrants do the same.

The second noteworthy result, given the focus of this paper, is the differences in the amount of worker reallocation within and across industries conditional on the experience of workers in the past. Of the 26% of stayers who moved, the reallocation across states of the world was roughly equal – about 1/3 changed jobs but stayed within the same industry, 1/3 changed industries, and 1/3 exited the workforce. The same pattern does not hold for other types of workers. In particular, of the 50% of job (but not industry) switchers who changed employers, over one half changed employers in the subsequent year (the balance either switched industries, or exited the core workforce). This transition matrix, then, begins to answer some of the questions raised in the introduction. Worker reallocation within industries is disproportionately accounted for by workers who have already been reshuffled within industries at least once; worker reallocation across industries is disproportionately accounted for by workers who have already been reshuffled across industries.

We also examine differences in exit rates. The most stable group of workers have an overall exit rate of about 9% (while some of this may be due to leaving the state, retiring, or pursuing an education, much is likely to be into unemployment). This rate stands in stark contrast to the least stable group of workers – those who entered the workforce within the past two years – almost one third (32% in Table 3) exit the workforce. This finding is consistent with worker-based surveys.

Status in t	Status in t+1				
	Job Stayers	Job Switchers within the same industry	Industry Switchers	Exiter	Total
Job Stayers	74%	10%	8%	9%	100%
Job Switchers within the same industry	50%	26%	13%	11%	100%
Industry Switchers	47%	14%	27%	12%	100%
Entrants	42%	12%	14%	32%	100%
Total	64%	11%	10%	12%	100%

⁷ In all the transitions estimated here, the priors are calculated from the first three years of the data (1991-1993) while the GCE estimator uses the rest of the data (1994-2001). All macro variables enter with one lag.

This transition matrix reflects the steady-state matrix for the full sample without controlling for demographics and macro-level indicators⁸. Table 4 presents the estimated matrix after including the controls described in the data section. A brief comparison reveals little difference between the two tables. We attribute this little difference to the fact that the period analyzed had a highly stable macro-economic activity level, and had no dramatic changes in the composition of the labor force. This is also consistent with evidence from U.S. data collected in the 1960's and 1970's which suggested that job turnover in general was not cyclical – the procyclical nature of layoffs was offset by the anticyclical nature of quits⁹.

Table 4: Estimated Transition Matrix for the Full Sample, controlling for macro-economic factors and demographic covariates					
Status in t	Status in t+1				
	Job Stayers	Job Switchers within the same industry	Industry Switchers	Exiter	Total
Job Stayers	73%	10%	8%	9%	100%
Job Switchers within the same industry	51%	25%	13%	12%	100%
Industry Switchers	47%	14%	27%	12%	100%
Entrants	42%	12%	14%	32%	100%

The results so far confirm the results in the literature in documenting that there are high rates of worker reallocation, both within and across industries, in the economy and that the reallocation varies substantially depending on the worker's employment history.

Our results on the persistence of within and across industry reallocation were not previously known, however. It is particularly interesting to note that workers who changed jobs within the same industry in the previous period have relatively high rates of industry switching in the subsequent period, although one might have expected them to try to stay within the same industry. In other work we have found that low-wage workers who work in low-wage industries tend to gain by switching out of that industry (Andersson et al, 2005); but that workers in higher wage, particularly high tech industries, tend to gain by staying within that industry (Brown et al., 2005). We investigate these results in more detail in Section 6, where we examine the individual probability of separation and include a measure of the return to tenure in the industry. We now turn to examining within and across industry reallocation in more detail.

5.3 Within and Across Industry Reallocation

Clearly the way in which employer-to-employer worker reallocation is decomposed into within and across industry allocation depends on the degree of industry

⁸ The macroeconomic variables that were used were the real interest rate; the growth rate of gross state income; and the state unemployment rate.

⁹ See, for example, Ehrenberg and Smith, Figure 10.4. To verify this for the 1950's and 1960's, plot NBER Series 08251b, Labor Turnover, Quit Rate, Manufacturing 01/1930-10/1968 against NBER Series 08252b, Labor Turnover, Layoff Rate, Manufacturing 01/1930-10/1968 between 1950 and 1968

detail chosen for the analysis. In this section, we examine this more closely, bearing in mind that this degree of accuracy and level of detail is only possible with a linked employer-employee dataset.

Table 5 decomposes the results from Table 4 – the shaded rows represent the sum of the middle two columns to calculate the employer-to-employer reallocation for each group of workers. The rows below each shaded row estimates the proportion of workers that changed industries at the two, three and four digit level of detail. The first row of the Table restates the 18% employer-to-employer reallocation for stayers reported in Table 5, and the row immediately below shows the proportion of these workers (cumulative from left to right) that also switched industry. The first cell indicates that almost half of these workers switched major industries at the time of the switch, suggesting that these workers went through a substantial industry reallocation. The last cell in that second row shows that some 27% (100% - 73%) of these workers stayed within the same narrowly defined industry, confirming the same substantial within-industry reallocation of production noted by Foster et al. (2001).

	One Digit	Two Digit	Three Digit	Four Digit
% of Job Stayers who switched jobs in subsequent period	18%			
- % who also switched industries	44%	63%	70%	73%
% of Entrants who switched jobs in subsequent period	26%			
- % who also switched industries	52%	73%	79%	82%
% of all firm (but not industry) switchers who switched jobs in subsequent period	41%			
- % who also switched industries	33%	46%	49%	51%
% of workers who switched firms and industries in previous period who switched jobs in subsequent period.	38%	36%	35%	35%
- % who also switched industries	67%	81%	85%	87%

The most salient results in Table 5, however, are evident in the last four rows. Individuals who switched jobs in the previous period, whether within or across industries, were much more likely to switch jobs in the current period than were either stayers or entrants. But across industry reallocation is much greater for those who were reallocated across industries in the previous period (the last set of rows) than for those who were reallocated within industries in the previous period (the third set of rows). This suggests that once an industry switch is made, workers are then still likely to shuffle from firm to firm to find the right match. We examine this result in more detail in section 6.

This section has demonstrated that there is a great deal of reallocation in the economy. About 26% of workers, who had previously exhibited a substantial degree of attachment to their employer reallocate in a given year. About two thirds of this reallocation

is within the economy, roughly evenly split between within and across broadly defined industries. We have found quite marked differences by demographic groups. And we have also found that a relatively small subset of workers is shuffled across jobs – both within and across industries – in the economy.

6. Firm-level reallocation and worker separations

In this section we exploit one of the strengths of the dataset, which enables us to directly link firm level reallocation and the probability of separation (switching industry, firm or exiting the workforce) for individual workers. Because we want to abstract away from other reasons for switching jobs, we choose to analyze the most stable group of workers: namely the subset of males who are 35-54 and who were employed by the same employer in the prior period (i.e. stayers in 1997 and 1998). We also choose one year in the middle of our dataset, 1998, which permits us both to make use of the individual fixed effects that have been calculated up to and including that year, and then examine outcomes in 1999. We describe the firm and industry characteristics in the preceding (1997) and reference (1998) year, and examine worker transition patterns one year afterwards – namely in 1999. We also control for the other factors that have been shown to be important determinants of separation from worker-based surveys, such as individual heterogeneity and firm size.

One of the most interesting results from the previous section was the substantial persistence in the patterns of reallocation. This suggests that tenure in the firm and the industry are important determinants of transitions, and since an additional advantage of our data is that we can calculate these measures with a great deal of precision, we include them not only as control variables but as measures of interest in their own right.

Another intriguing result was the high degree of worker reallocation across industries. One possible reason for this (as suggested by Mincer and Polachek 1977, although in a different context) is that workers are likely to move out of industries with low returns to tenure in order to improve their lot. In order to identify low tenure industries, we ran Mincerian earnings regressions on an industry by industry basis. We used the results from these regressions to calculate the return to tenure 5 years and then classified industries as high or low tenure depending on whether the estimated return to tenure (after five years) in each industry was above or below the economy-wide average. Figure 1 provides a visual description of which industries were classified as above or below the average – which is shown by the horizontal line on the graph.

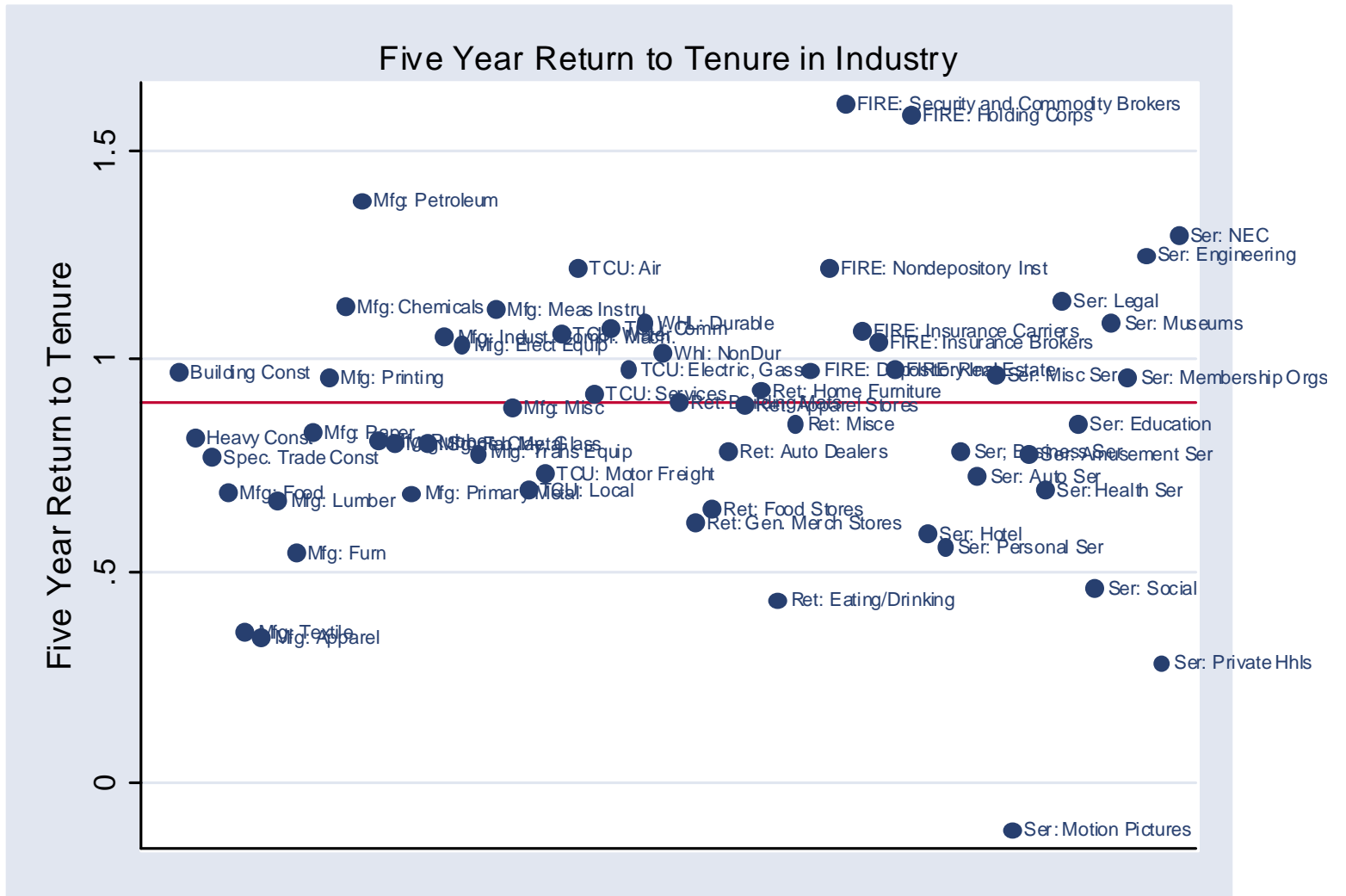


Figure 1: The Five Year Return to Industry Tenure

Table 6 provides some summary statistics on firm and industry characteristics of the 1997 employers of 1998 workers. Workers who stayed with the firm in 1998 were much less likely to work in 1997 for either a high job destroying or high churning firm than either firm or industry switchers. Stayers also worked for firms with a higher return (a higher fixed effect) and were less likely to work in low tenure industries. Firm switchers, by contrast, were the most likely to work for high job destroying firms, with high churning rates, and in low tenure industries.

Table 6: Summary Firm and Industry characteristics of employer in 1997					
Worker transition in 1998	High Job Destruction	High job creation	High churning rate	Low tenure industry	Firm fixed effect
Across Industry Allocation <i>Industry Switcher</i>	10.35%	8.14%	74.40%	62.67%	.002
Within Industry Reallocation <i>Firm Switcher</i>	23.73%	7.15%	83.28%	70.47%	.032
Stayer	1.87%	7.03%	46.89%	56.77%	.068

Our next task is to empirically estimate the impact of firm and industry characteristics, particularly reallocation rates, on the probability of workers separating (and whether they separate to go to another industry or another firm) in subsequent years (1999, 2000 and 2001), conditional on the worker having been a stayer in 1998. We use a multinomial logit framework to address this, and report the estimated marginal effects in Table 7. These results are reported in terms of relative risk ratios, with the comparison group being the group of stayers. It is worth noting that we control here for individual heterogeneity (estimated over the period up to and including 1998) by means of including the individual fixed effects described in the data section and in Abowd et al (2003).

An examination of the first two sets of rows in Table 7 reveals that workers with greater firm tenure are less likely to leave their firm, industry and employment, while workers with greater industry tenure are more likely to reallocate within their industry (i.e. leave their firm but not their industry or employment). The third set of rows makes it clear that at least a partial driver of this is the low return to tenure within an industry – which tends to increase both within and across industry reallocation as well as exit from employment.

We find that that the reallocation rate of the employer in 1997 and 1998¹⁰ is an important driving force. While higher job creation and destruction rates of the employer in 1997 slightly increased the odds of within and across industry reallocation in 1999, the most important factor was whether the firm was a job destroyer or creator in 1998. Employment in an expanding firm in 1998 substantially reduced the likelihood of both within and across industry reallocation about equally; but employment in a contracting firm in 1998 increased the likelihood of within industry reallocation much more than

¹⁰ Recall that since the estimate is for workers who were classified as “stayers” in 1998, they have the same employer in both 1997 and 1998.

across industries. Employment in high churning firms – either in 1997 or 1998 – also increased the likelihood of reallocation across and within industries about equally¹¹.

Table 7: The relative marginal effects of firm and industry characteristics on separations (by type of separation)			
	Within Industry Allocation <i>Firm Switcher in 1999 (same 2-digit SIC)</i>	Across Industry Reallocation <i>Industry Switcher in 1999</i>	Exiters in 1999
Tenure in firm in 1998	-.3030*	-.1437*	-.1237*
	(.0023)	(.0023)	(.0026)
Tenure in 2-digit industry in 1998	.1471*	-.1447*	-.1494*
	(.0023)	(.0021)	(.0025)
1997-1998 industry has low return to tenure	.3545*	.01528*	.0861*
	(.0075)	(.0060)	(.0071)
1997-98 employer destroyed jobs during 1997	.1741*	.1593*	.0534*
	(.0071)	(.0059)	(.007)
1997-98 employer destroyed jobs during 1998	1.1277*	.7036*	.655*
	(.0069)	(.0055)	(.0066)
Employer is High Churning in 1997	.1999*	.1900*	.0926*
	(.0087)	(.007)	(.0083)
Employer is High Churning in 1998	.36826*	.3129*	.3548*
	(.0087)	(.007)	(.008)
Constant	-2.366*	1.0853*	.0744
	(.0426)	(.0319)	(.0384)
Number of observations: 153,1119; controls for firm size, firm fixed effect as well as individual age and age squared and individual fixed effect; standard errors in parentheses			

In sum, we have found that firm level job and worker reallocation still substantially increases the probability of transition for even the most stable group of workers, even after controlling for individual characteristics and firm and industry tenure. We confirm the importance of tenure that was suggested by the descriptive statistics presented in Section 5. And we find that workers who are employed in industries that provide low returns to tenure are much more likely to reallocate both within and across industries.

¹¹ We categorize the firms for which they work as job creating or destroying if those rates exceed 20%, and high churning if those rates exceed 20%. We use the churning rate defined in Burgess et al. (2000) – the worker flow rate less the absolute value of the job reallocation rate

7. Summary and Conclusions

We began by asking two basic questions

1. What is the “equilibrium” amount of worker reallocation in the economy – both within and across industries as well as by different demographic and income groups?
2. How much does firm-level job reallocation affect the separation probabilities of workers?

We established a set of facts about the amount of worker reallocation in the economy. We were able to confirm that, even among a relatively stable group of workers, there is a great deal of reallocation. About 26% of workers, who had previously exhibited a substantial degree of attachment to their employer reallocate in a given year. About two thirds of this reallocation is within the economy, roughly evenly split between within and across broadly defined industries. Given the differences in datasets, estimation techniques and definitions, this is remarkably similar to results achieved by Fallick and Fleischmann (2004).

Further, this paper went beyond establishing these sets of facts. We confirmed the results from worker-based surveys in finding quite marked differences by demographic groups. Older workers are much less likely to be reallocated and more likely to exit than are younger workers. Groups of workers that have experienced high degrees of turbulence in prior years are much more likely to experience turbulence in the next period.

We also find that firm level job and worker reallocation still substantially increases the probability of transition for even the most stable group of workers, even after controlling for individual characteristics and firm and industry tenure. And, intriguingly, workers who are employed in industries that provide low returns to tenure are much more likely to reallocate both within and across industries.

But the main contribution of the paper was to establish the order of magnitude of within and across industry worker reallocation using a detailed large-scale dataset. We found that a relatively small subset of workers was shuffled across jobs – both within and across industries – in the economy. Although the levels of reallocation varied across demographic group, the basic pattern of persistence did not.

These results have implications not only for estimates of the order of magnitude of friction in the economy, but also raise questions about how much of the reallocation process is driven by the characteristics of the workforce, how much is driven by the production process of firms, and how much by the history of workers caught up in the interaction of the two forces.

We will investigate these issues in our subsequent research. In particular, we will focus on estimating the sources of differences in within and across industry allocation by

investigating the degree to which there is an interaction between industry complexity and the types of workers that are reallocated.

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Appendix – The Estimation Method

A.1 The Basic Worker Reallocation Model

To model the transition process with our data, we proceed as follows. Let \mathbf{y}_t be a K -dimensional vector of proportions in the j^{th} Markov state in period t . Similarly, let \mathbf{y}_{t-1} be a K -dimensional vector of proportions in the k^{th} Markov state in period $t-1$, where \mathbf{y} is the vector of shares calculated directly from the data at each period $t=1, 2, \dots, T$. Next, define the (equilibrium) $K \times K$ matrix of probabilities $P = (p_{kj})$ representing the probability of moving from state k to state j in the next period. In this work we use $K=5$. With these data (\mathbf{y}), our objective is to estimate (with minimal distributional or structural assumptions) the first order Markov transition probabilities for the entire population, for each demographic group, and for any other sub-group of interest.

Following, the literature, the basic relationship between period $(t-1)$ and period t is captured via the $K \times K$ matrix of transition (reallocation) probabilities

$$y_{ij} = \sum_{k=1}^K p_{kj} y_{t-1,k} \quad \text{with} \quad \sum_{j=1}^K p_{kj} = 1 \quad \text{for } j, k = 1, 2, \dots, K \quad (1)$$

Taking into account the noise in the observed data, the correct noisy observed model (or the stochastic set of empirical moments) is

$$y_{ij} = \sum_{k=1}^K p_{kj} y_{t-1,k} + \varepsilon_{ij} \quad (2)$$

where ε_{ij} represents the noise in the data. Since y_{ij} is either 0 or 1 in this model, each ε_{ij} is naturally bounded in $[-1, 1]$, with expected mean value of zero. We now extend this basic framework to allow for additional covariates.

In addition to the information on the proportion of individuals in the k^{th} state in time t , we also incorporate socio-economic and macroeconomic variables. Let \mathbf{x}_{tk} be a G -dimensional vector of socio-economic covariates with individual elements x_{gtk} . In this model the covariates are represented in terms of shares. Thus, x_{gtk} is the mean value of covariate $g=1, 2, \dots, G$, at time period $t=1, 2, \dots, T$, in state $k=1, 2, \dots, K$. In addition, for each period t , let \mathbf{s}_t be an L -dimensional vector of macro-level variables.¹² It is important to note that the demographic covariates vary by both state and time while the macro-level variables vary only by time. The exact functional relationship describing the effect of these two types of variables (X and S) on the transition probabilities is unknown. Therefore, to capture the inter-relationship between the observed data, \mathbf{y} , the unknown

¹² The macro-level variables may include macroeconomic, industry/market, and policy variables that either directly or indirectly affect the transition matrix. For example, changes in national or regional income, oil shocks, or large swings in the interest rates.

probabilities P , the covariates X , and the global variables S , we introduce the following (cross moments) relationship

$$\begin{aligned} \sum_{t=2}^T y_{ij} x_{gtj} s_{lt} &= \sum_{t=2}^T \sum_{k=1}^K p_{kj} y_{t-1,k} x_{gt-1,k} s_{lt-1} + \sum_{t=2}^T \varepsilon_{ij} x_{gtk} s_{lt} \\ &= \sum_{t=1}^{T-1} \sum_{k=1}^K p_{kj} y_{tk} x_{gtk} s_{lt} + \sum_{t=2}^T \varepsilon_{ij} x_{gtk} s_{lt} \end{aligned} \quad (3)$$

The global (macro-level) variables enter as lag variables where the empirical results will determine the exact variables used. For example, the decision whether to use the difference in the unemployment rates, or just the lag unemployment rate, or maybe the lag unemployment and the unemployment two periods in the past is an empirical question that is sorted out in the empirical part.

A.2 The Information-Theoretic Estimation Model

Our objective is to estimate the transition matrix P with minimal distributional assumptions. To do so, we treat both the transition probabilities P and the error components ε as two sets of unknowns. But before constructing the estimation method, it is important to realize that this basic problem (Eq. 1, or Eq. 2 or Eq. 3) is under-determined. There are infinitely many P 's that satisfy these equations. Therefore, we need to either add more structure, or choose a certain criterion that will allow us to choose one of the infinitely many solutions that satisfy these data. In the work here, we follow the Information Theoretic (IT) - Generalized Maximum Entropy (GME) philosophy and use the (Shannon) entropy as the criterion. Since the entropy function is defined on proper probability distributions we first reformulate the noise components ε_{ij} as a set of proper probabilities defined on some support space ν . For more detailed background on the GME and related work, see Golan, Judge and Miller (1996) and Golan, Judge and Perloff (1996). For background and recent work on IT and its relationship to GME and other methods of estimation and inference see special issue of the Journal of Econometrics (2002).

Rewriting Eq. (3) yields

$$\begin{aligned} \sum_{t=2}^T y_{ij} x_{gtj} s_{lt} &= \sum_{t=1}^{T-1} \sum_{k=1}^K p_{kj} y_{tk} x_{gtk} s_{lt} + \sum_{t=2}^T \varepsilon_{ij} x_{gtk} s_{lt} \\ &= \sum_{t=1}^{T-1} \sum_{k=1}^K p_{kj} y_{tk} x_{gtk} s_{lt} + \sum_{t=2}^T \sum_{m=1}^M w_{ijm} v_m x_{gtk} s_{lt} \end{aligned} \quad (4)$$

with $\sum_{m=1}^M w_{ijm} = 1$ and where $\varepsilon_{ij} \equiv \sum_{m=1}^M w_{ijm} v_m$ for $M \geq 2$. Since $\varepsilon_{ij} \in [-1, 1]$ for all t, j , then $v_m \in [-1, 1]$ and ν is a symmetric around zero support space for each random error defined above. In our empirical analysis, we use $M=3$. We also experimented with $M=5$, $M=7$ and higher values, but all yielded practically the same estimates. We note that even

though, the support can be defined as continuous, in this work we work with the discrete support defined above.

By now, we have reformulated the basic Markov model to include all of the available information (socio-economic and global). We also have converted the unknown errors to be fully represented by a set of proper probabilities $W = (w_{ijm})$, so all of the unknown quantities here (P and W) are proper probability distributions. We can now construct the GME estimation method which maximizes the joint Shannon (1948) entropies of the signal, P , and the noise, W , subject to the available information (the data) and the requirement that both P and W are proper probability distributions.

However, rather than working with the GME, we are interested in extending the model such that it can incorporate prior information representing some prior knowledge or belief on the Markov probabilities P , call it P^0 . These priors may come from prior data, theory, and/or other experiments. To accomplish that, we substitute the entropy objective (of the GME-type model) with the cross-entropy, or Kulback-Liebler information-divergence measure. Thus, our IT-Generalized Cross Entropy (GCE) workers allocation Markov estimation model is

$$\begin{aligned}
 & \text{Min } \left\{ \sum_{k,j} p_{kj} \log(p_{kj} / p_{kj}^0) + \sum_{ijm} w_{ijm} \log(w_{ijm} / w_{ijm}^0) \right\} \\
 & \{p, w\} \\
 & \text{s.t.} \\
 & \sum_{t=2}^T y_{ij} x_{gij} s_{it} = \sum_{t=1}^{T-1} \sum_{k=1}^K p_{kj} y_{tk} x_{gik} s_{it} + \sum_{t=2}^T \sum_{m=1}^M w_{ijm} v_m x_{gik} s_{it} \\
 & \sum_j p_{kj} = 1; \sum_m w_{ijm} = 1
 \end{aligned} \tag{5}$$

The only difference between the GME model and the GCE model (5) is that under the GCE model the posterior estimates are those probabilities that are consistent with all of the constraints (data) and are closest to the priors. Constructing the Lagrangean and solving (5) yields the optimal solution

$$\tilde{p}_{kj} = \frac{p_{kj}^0 \exp\left(\sum_{t=1}^{T-1} \sum_{g,l} y_{tk} x_{gik} s_{it} \tilde{\lambda}_{jgl}\right)}{\sum_j p_{kj}^0 \exp\left(\sum_{t=1}^{T-1} \sum_{g,l} y_{tk} x_{gik} s_{it} \tilde{\lambda}_{jgl}\right)} \equiv \frac{p_{kj}^0 \exp\left(\sum_{t=1}^{T-1} \sum_{g,l} y_{tk} x_{gik} s_{it} \tilde{\lambda}_{jgl}\right)}{\Omega_k} \tag{6A}$$

and

$$\tilde{w}_{ijm} = \frac{w_{ijm}^0 \exp\left(\sum_{g,l} x_{gtk} s_{lt} v_m \tilde{\lambda}_{jgl}\right)}{\sum_m w_{ijm}^0 \exp\left(\sum_{g,l} x_{gtk} s_{lt} v_m \tilde{\lambda}_{jgl}\right)} \equiv \frac{w_{ijm}^0 \exp\left(\sum_{g,l} x_{gtk} s_{lt} v_m \tilde{\lambda}_{jgl}\right)}{\Psi_{ij}}, \quad (6B)$$

where $\tilde{\lambda}_{jgl}$ are the $(K \times G \times L)$ estimated Lagrange multipliers associate with the data (Eq. 4), and the estimated noise components are $\tilde{\varepsilon}_{ij} = \sum_m \tilde{w}_{ijm} v_m$. Note, that the priors for the noise terms are *always taken to be uniform*.

Instead of using the constrained optimization estimation model (5), the IT-GCE can be formulated as an unconstrained, concentrated (or a generalized likelihood) model:

$$\begin{aligned} \ell(\boldsymbol{\lambda}) &= \sum_{t=2}^T \sum_{j=1}^K \sum_{s,g} y_{tk} x_{gtk} s_{lt} \lambda_{jgl} - \sum_k \log \left[\sum_j p_{kj}^0 \exp\left(\sum_{t=1}^{T-1} \sum_{g,l} y_{tk} x_{gtk} s_{lt} \lambda_{jgl}\right) \right] \\ &\quad - \sum_{i,t,j} \log \left[\sum_m w_{ijm}^0 \exp\left(\sum_{g,l} x_{gtk} s_{lt} v_m \lambda_{jgl}\right) \right], \quad (7) \\ &= \sum_{t=2}^T \sum_{j=1}^K \sum_{s,g} y_{tk} x_{gtk} s_{lt} \lambda_{jgl} - \sum_k \log \Omega_k(\boldsymbol{\lambda}) - \sum_{t,j} \log \Psi_{ij}(\boldsymbol{\lambda}) \end{aligned}$$

where both normalization factors $\Omega_k(\boldsymbol{\lambda})$ and $\Psi_{ij}(\boldsymbol{\lambda})$ are defined in (6) above, and $\boldsymbol{\lambda}$ is the set of $(K \times G \times L)$ Lagrange multipliers which are the *real* set of unknown and unobserved quantities in this model. Maximizing (7) and solving for $\boldsymbol{\lambda}$, yields the estimated $\tilde{\boldsymbol{\lambda}}$, which in turn yield the optimal probabilities \tilde{p}_{kj} and \tilde{w}_{ijm} via relationship (6).

It is important to note that this model is computationally as efficient as the maximum likelihood (ML) approach. In fact it is a generalized ML-logit method with flexible “moment requirements” and with priors. The solution to the IT-GCE problem converges to the ML-logit solution as the noise approaches zero. As a result, the conventional ML-logit solution is a special case of model (5), or (7), when all estimated errors in equation (4) are zero and where the priors are all assumed to be uniform. The first condition exists, however, if, and only if, the Markov process is perfectly stationary, and there is no noise in the data; two assumptions that are generally inconsistent with the available data and economic structure. Moreover, because all of the estimates are unique functions of the Lagrange multipliers, $\boldsymbol{\lambda}$, this method has the same level of complexity as the traditional ML.