Job Flows, Worker Flows, and Churning

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We utilize a large employer-level panel dataset to explore the links between gross job flows and gross worker flows. Our findings have relevance for models of job creation and job destruction, and labor reallocation. We find churning flows (the difference between worker and job flows at the level of the employer) to be high, pervasive, and highly persistent within employers, suggesting that they arise as a correlate of an equilibrium personnel policy. We find the dynamic relationship between job and worker flows to be quite complex: lagged job flows raise churning flows, and lagged churning flows reduce employment growth.

I. Introduction

The analysis of the reallocation of labor currently has two major strands. The search and matching approach is about worker flows. The...
set of articles on job creation and job destruction is about job flows. These two literatures have largely developed along separate tracks. Yet their synthesis is essential to an understanding of labor market dynamics and the reallocation of labor in general and unemployment in particular. This article advances this synthesis by exploring the empirical relationship between job and worker flows at the employer level.

The relationship between aggregate job and worker flows is nontrivial, although most models assume them to be equal. Furthermore, recent microeconometric evidence from Hamermesh, Hassink, and van Ours (1996) and Lane, Stevens, and Burgess (1996) has shown that behavior at the microlevel is complex: shrinking employers engage in hiring and growing employers fire workers.

In this article, we use the term worker flows to refer to all movements of workers into and out of jobs. Job flows measure the gross creation and destruction of jobs, reflecting the expansion and contraction of establishments. The numerical difference between these two flows we label as "churning flows." These could arise from workers quitting and being replaced (workers churning employers), and/or simultaneous hiring and firing by employers (employers churning workers) to improve the quality of their workforce or to reconfigure their skill mix. These issues and labels are discussed in more detail below. In other words, churning refers to match heterogeneity over and above the employer heterogeneity identified by the job reallocation literature. We believe that the distinction between job flows and churning flows isolates the two fundamental processes underlying job and worker reallocation. These are the reevaluation by the employer of the number of job slots it wants and the reevaluation by both parties of the match of a particular job slot and a particular worker. Thus, worker flows have two components: those which are an immediate consequence of job creation and destruction and those in excess of job flows. The second component, which is what we call churning flows, could be the result of random mismatches or could be an equilibrium phenomenon. In this article, we show that churning is not the response to an unfortunate mismatch, scattered randomly across employers, but is highly persistent in particular employers suggesting that it is an equilibrium phenomenon, associated with a particular set of optimal personnel policies.

We investigate whether there is time-series variation in churning. It is possible, for example, that a burst of net hiring will increase the number of workers of unknown quality and may lead to higher subsequent churning. In order to explore this, we examine the dynamic relationship

\[ \text{This includes articles such as Leonard (1987); Dunne, Roberts, and Samuelson (1989); Davis and Haltiwanger (1990, 1992); and Davis, Haltiwanger, and Schuh (1996).} \]
between job flows and churning flows employer-by-employer finding, among other things, that past employment growth does indeed have a significant effect on current churning.

Cutting the data this way, into job and churning flows, yields a number of new facts, which we set out below. The article is organized as follows: Section II briefly describes the data (details are in the appendix) and the framework we use to interpret the results; Section III presents the results. Finally, Section IV concludes.

II. Preliminary Issues

In this section, we briefly review some previous work on this topic, describe the dataset, set up the notation, and discuss the economic decisions underlying churning.

A. Previous Work

There is a great deal of work on the matching approach to labor markets, and also on gross job flows (see, e.g., the references in fnn. 1 and 2). Few articles, however, address both worker flows and job flows together. One exception is Mortensen and Pissarides (1994), who introduce a job creation and destruction process into a matching framework. Even so, their assumptions imply that total hires equal total (gross) jobs created, total separations equal total (gross) jobs destroyed, and so total job flows equal total worker flows. There is a little empirical work but some has had to rely on less than ideal datasets. For example, Davis, Haltiwanger, and Schuh’s (1996) data contain no information on workers, and so they are forced to combine a number of different data sources; Blanchard and Diamond (1990) face the same problem; Anderson and Meyer’s (1994) study of separations and postseparation experience provides much useful evidence on the importance of job flows for worker flows, but it uses a worker-based dataset.

Of those using appropriate datasets, the study by Hamermesh et al. (1996) does not have a long panel element. Burda and Wyplosz (1994) use aggregate data to display the gap between job and worker flows for Germany and discuss other aggregate findings. The ideal dataset for this problem is based on the universe of employers (job flows are defined on employers), matched with the universe of workers. We are able to exploit a long panel of such data to extend our earlier research (Lane et al. 1996) on both job flows and worker flows.

B. Data

The database is drawn from the universe of Maryland quarterly wage reports; we describe it in detail in the data appendix. Maryland collects quarterly information about employee earnings from employers who report in compliance with its unemployment compensation law. This
includes everyone employed in Maryland except for those who are self-
employed, who work for certain nonprofit organizations, or who work on family farms or as seasonal or migrant farm workers. Employers who are required to comply with the state's unemployment compensation law include virtually all employers of one or more paid employees. The only major excluded employers are the federal government, self-employed individuals, some small agricultural enterprises, and philanthropic and religious organizations. Employment of individuals who receive no salary at all, who are totally dependent upon commissions, and who work on an itinerant basis with no fixed location or home base is not reported by covered employers. State and local government employment is reported.

There are roughly 1.5 million employees every quarter and over 100,000 reporting units (90% of these reporting units are single-establishment entities: see the appendix for details; for brevity, we refer to them as employers from now on). Our database consists of these records from 1985:3-1994:3 and complementary four-digit standard industrial classification (SIC) codes. A vintage data element identifies the year/month when each business enterprise first acquired an unemployment compensation account number in the state, dating back to 1938. The unit of observation is an employer-quarter.

Similar data have been used in other contexts. Leonard (1987) was one of the first to use Wisconsin data to examine frictional and structural unemployment; Topel and Ward (1992) used Unemployment Insurance (UI) wage records to track the earnings history of young men; Jacobson, Lalonde, and Sullivan (1992) exploited Pennsylvania data to track the impact of job loss on displaced workers. Anderson and Meyer (1994) have addressed turnover issues using the Continuous Wage and Benefit History dataset, which is derived from eight state UI systems, but which is focused on worker, rather than employer, records.

Our data on worker turnover yield similar results to those found by the closest research on a similar dataset. For example, Anderson and Meyer (1994, p. 193) find an accession rate of 15.9%; in our dataset, the figure is 16.2%. They calculate an accession less recalls rate of 12.0%, compared to the figure in our dataset of 14.0%. In their dataset, 23.0% of matches last less than 1 quarter; in the Maryland dataset, the figure is 22.4%. Our figures on job reallocation are similarly quite close to the rates noted by Davis, Haltiwanger, and Schuh (1996). In fact, Davis and Haltiwanger (1999) discuss in detail issues of comparability between the longitudinal research database (LRD) and UI records datasets and argue that they produce comparable results. Indeed, their year-to-year job 19.4% job reallocation rate in U.S. manufacturing is matched by our year-to-year rate of 18.3% for Maryland manufacturing.

See also Davis et al. (1996), p. 35, fn. 14, and p. 185.
One consequence of our having almost the universe of employment is that the data include all individual employment spells with an employer, of whatever duration. If, however, we describe all hires and separations, this will result in very short employment spells dominating the picture (as just noted, 22% of employment spells in our data dissolve within a quarter). An analysis of these short spells is of interest in its own right, but as Anderson and Meyer point out, although short spells characterize the average job, long spells characterize the average person's current experience. We explicitly and deliberately focus on nonephemeral jobs, which we define as those lasting at least a quarter. All flows and stocks described below are of people into and out of jobs lasting at least a full quarter. It seems likely that including all shorter spells would in fact give rise to much higher churning, enhancing the case we are making here, but the increased noise from many very short employment spells would also probably blur the main points we wish to make.

By the same token, we make a positive sample selection decision on employers' size. It is usual in studies of job flows to have a minimum employer size for inclusion; usually, this is imposed by the dataset, but here we can choose, and we take employers with at least five employees. This enables us to focus on the decision-making processes of the employers who employ 94% of the workers in our dataset.

### C. Terminology

Employment at employer $i$ at time $t$ is denoted $E_{it}$. In calculating rates, we follow Davis and Haltiwanger (1990) in using as the denominator the average of current and past employment, denoted $N_{it} = (E_{it} + E_{i,t-1})/2$. Job flows refer to the change in employment: $JF_{it} = E_{it} - E_{i,t-1}$ and job reallocation is the absolute value of job flows, $JR_{it} = |JF_{it}|$. Job creation (JC) is a positive job flow, job destruction (JD) is a negative job flow: $JC_{it} = JR_{it}$ if $JF_{it} \geq 0$, $JD_{it} = JR_{it}$ if $JF_{it} < 0$. The corresponding rates ($JCR_{it}$, $JRR_{it}$, $JCR_{it}$, $JDR_{it}$) are the levels divided by $N_{it}$. The aggregate numbers on job flows that we report are, as in Davis and Haltiwanger (1990), simply the sum of jobs created, destroyed, and reallocated divided by the aggregate employment level.

Total worker flows are defined as the sum of hires and separations, $WF_{it} = H_{it} + S_{it}$. Job flows are clearly $JF_{it} = H_{it} - S_{it} = E_{it} - E_{i,t-1}$. Worker flows can thus be written as $WF_{it} = JR_{it} + CF_{it}$ where $CF$ is the level of excess worker flows, or churning. The first of these components, $JR$, is the counterpart to job flows and is necessary to accomplish the employer's growth or decline. This is the job reallocation component that has been studied by others (Leonard 1987; Dunne, Roberts, and Samuel-

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4 In this we follow the example of Topel and Ward (1992).
5 Recall that this is the total of all nonephemeral jobs (lasting at least 1 quarter).
son 1989; Davis and Haltiwanger 1990, 1992; Anderson and Meyer, 1994; Organization for Economic Cooperation and Development [OECD] 1994). The second of these, CF, is worker flows in excess of job flows, which we call churning and is the focus of the subsequent section. It represents the difference between labor reallocation and job reallocation and can arise from employers churning workers or workers quitting and being replaced.6

The introductory example can be used to illustrate these definitions. Suppose an employer of 100 employees increases employment by 10 and this is achieved by 15 hires and 5 separations. The job flow JF is +10 (15 hires − 5 separations), as is the job reallocation flow JR. The worker flow WF is 20 (15 hires + 5 separations), and the churning flow CF is 10 (WF − JR). Job creation JC is 10 and job destruction JD is 0. The corresponding rates are JFR = 0.095[10/(1/2(100 + 110))], JRR = 0.095, WFR = 0.190, and CFR = 0.095. There are, thus, 10 jobs but 20 workers reallocated, and a focus on job reallocation alone would miss much of the labor reallocation.

Before turning to the analysis, we discuss the mapping of the concepts of job flows and churning flows on to the data available to us and the precise algebraic definitions set out above. Our worker flows measure, summing hires and separations, measures all movements of workers into and out of jobs. The distinction within this total between job and churning flows is less clear-cut and depends on what is meant by a “job” and, in the end, by data constraints. Our definition of job flows is the standard one: the net change in employment at the employing unit. This is, perhaps implicitly, based on the notion of the job as a relationship (a contract) between a worker and an employer, that is, simply a worker-employer match. Changes in the number of such matches is what we can measure and what we mean by job flows. All other flows of workers are then necessarily labeled as churning flows. But another, equally valid, view of a job links it to a task, a particular set of skills. Thus when a firm reconfigures its skill mix keeping the total number of jobs the same, replacing jobs of one type (one task, one skill type) with jobs of another type, under this view there would be both job creation and job destruction. Note that given our framework and our data, such changes would be counted as churning flows with zero job flows. This is a well-known problem with available employer-level datasets: in their book, Davis et al. (1996, p. 191) say: “Since the LRD does not identify individual jobs at a

6 One component of worker flows is temporary layoffs and recalls. In this article, we treat these no differently from other flows (Anderson and Meyer [1994] discuss the proportion of temporary layoffs in total separations). The ability to engage in temporary layoffs differs between industries and this also will be reflected in the churning figures. Given that we can identify ex post recalls, in future work we intend to quantify this contribution to churning differences.
plant, some newly created and newly destroyed jobs may not show up as plant-level employment changes. For example, a plant may destroy ten assembler jobs and create ten robotics technician jobs, so that total employment does not change. In this respect, [their measures] understate the true levels of gross job creation and destruction.” The result of all this is that from one perspective, the job flows we report are understated and the churning flows overstated.

D. Framework

Churning can be seen as the reevaluation of a job match, initiated either by an employer, and evidenced by simultaneous hiring and firing, or by an employee, and evidenced by the replacement of quits. This reevaluation is an investment decision in which the agent compares the cost of changing a partner with the discounted benefit stream. The dynamic programming approach of search theory is applicable to this setting, with both parties setting a reservation match value level. However, if some aspects of a match are “experience goods” rather than “inspection goods,” they can only be observed once a match has been made. The value of the match will evolve as its “experience” characteristics become apparent: the working conditions as viewed by the worker; the motivation and true ability of the worker as viewed by the employer. The decision to maintain or dissolve the match then needs to be reviewed continuously by both the worker and the employer. The decision by either side that they wish to change partners but remain in the same state (for the worker: remain employed; for the employer: keep the same employment level) produces churning flows. We would expect churning flows to vary between employers and over time.

Cross-sectional variation in churning arises from the conjunction of the employer’s optimal personnel policy and the stochastic processes governing the evolution of the match value. The environmental parameters that will influence the employer’s personnel policy include turnover costs, the nature of the technology, skill requirements, and managerial matching ability. There are a number of issues here. For some employers, turnover costs are high and so the best strategy is to put a lot of effort into matching/hiring and consequently churning will tend to be lower; for low-turnover-cost employers, it may be better to hire almost anyone and sort through the stock whilst they are employed. Other factors include the degree to which skills are observable prior to employment, the relative costs of false negatives and false positives, and the frequency with which

7 More detail on these arguments is provided in Burgess, Lane, and Stevens (1994).
8 See Jovanovic (1979) and McLaughlin (1991).
9 We are grateful to Michael Burda for this description.
the employer needs to change technology and, hence, skills. It also may be
the case that in some employers there is value in a constant inflow of new
blood into an employer. Finally, it is also possible that managers differ in
their ability to select well-matched applicants.10

Over time, the employer’s planned employment changes may influence
churning: when firing, the employer will select the lowest quality (lowest
match value) workers; when hiring, they will draw from the distribution
represented in the current hiring pool. So increases in the employer’s
employment level in the recent past will mean an influx of people of
uncertain quality, generating an increase in churning, and recent negative
job flows mean that the employer has just had a chance to sort through
its quality distribution, therefore reducing the need for current churning.

We now briefly consider the reverse question, namely, the possible
effect of churning flows on job flows. Here there is a less obvious model
to use, since we do not have a standard model of the determination of
gross job flows (contenders include Davis and Haltiwanger 1990; Cabal-
lero and Hammour 1994; Mortensen and Pissarides 1994).11 These models
do not include a discussion of churning; the excess of worker flows over
and above job flows. In the absence of a formal model, we simply
highlight two issues suggesting opposite conclusions. First, efficiency
wage models often stress the deleterious effects on an employer of excess
turnover (Salop 1979). If CFR contains a large component of quit re-
placement, then it could be that high CFR will negatively affect job
growth. This view suggests that the employer has chosen the wrong
personnel/recruitment strategy and is suffering as a result. Second, it
could be that the employer chooses to improve the quality of its work-
force before an anticipated expansion: certainly the reservation match
value level of the employer will depend on its view of its future prospects.
The consequent higher churning would then be associated with higher
productivity and better prospects for the employer’s growth.

III. Results

We present our results under two main headings. First, we set out the
main features of interest in the data. These include the cross-sectional
distribution of the flows, the time-series features, and an investigation of
the nature of the employer-level heterogeneity evident in our data. Sec-
ond, we study the dynamic interrelationship of job and churning flows at
employer level. The results are based on data from around 1.15 million
workers (27,000 employers) per quarter in nonmanufacturing and 129,000

10 See Lane, Isaac, and Stevens (1996) for more details.
11 One can argue that job creation and job destruction are simply labor demand
writ small; for this, of course, there is a vast literature for which we simply
reference Hamermesh (1993). It is still the case, however, that most of this
literature does not consider the effect of churning on labor demand.
workers (1,700 employers) per quarter in manufacturing (precise numbers are given in the tables 1–8).

A. Features of the Data

1. Cross-Sectional Features

The discussion above suggests the importance of the idiosyncratic component of churning, but churning levels, and their contribution to labor reallocation, are unknown a priori. An analysis of the distribution of worker and job flows reveals a considerable amount of labor reallocation, primarily due to churning. Table 1 gives the results for nonmanufacturing and table 2 provides the same information for manufacturing industries.

Taking nonmanufacturing first, a mean worker flow (hires plus separations) rate of 32.3% per quarter indicates a vast amount of labor reallocation. One in three job matches in nonmanufacturing either forms or breaks up each quarter. Note that the worker flow rate is constructed as the sum of hiring and separation rates to make it analogous to the job reallocation rate, so this figure is equivalent to balanced hiring and separations of 16.15% per quarter.

The worker reallocation rate is the sum of a job reallocation rate of 9.5% per quarter and a churning rate of 22.8%. The main feature of interest is the very high churning flow rate, indicating an enormous amount of worker reallocation over and above that occasioned by job reallocation (recall the comment above that this measure of churning includes personnel changes arising from skill reconfiguration). The table also shows that the churning rate generally declines with the age and size

Table 1
Job and Worker Reallocation in Nonmanufacturing

<table>
<thead>
<tr>
<th>Worker Flow Rate</th>
<th>Job Reallocation Rate</th>
<th>Churning Rate</th>
<th>Flows/Worker Flows</th>
<th>No. of Workers (Employers)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>.323</td>
<td>.095</td>
<td>.228</td>
<td>.704</td>
</tr>
<tr>
<td>Employment ≤ 50</td>
<td>.414</td>
<td>.150</td>
<td>.264</td>
<td>.639</td>
</tr>
<tr>
<td>50 &lt; employment ≤ 100</td>
<td>.422</td>
<td>.114</td>
<td>.309</td>
<td>.730</td>
</tr>
<tr>
<td>100 &lt; employment ≤ 500</td>
<td>.382</td>
<td>.094</td>
<td>.289</td>
<td>.754</td>
</tr>
<tr>
<td>500 &lt; employment ≤ 1,000</td>
<td>.300</td>
<td>.078</td>
<td>.223</td>
<td>.742</td>
</tr>
<tr>
<td>1,000 &lt; employment</td>
<td>.169</td>
<td>.045</td>
<td>.125</td>
<td>.767</td>
</tr>
<tr>
<td>Age ≤ 5 years</td>
<td>.513</td>
<td>.152</td>
<td>.361</td>
<td>.704</td>
</tr>
<tr>
<td>5 &lt; age ≤ 12</td>
<td>.316</td>
<td>.096</td>
<td>.221</td>
<td>.698</td>
</tr>
<tr>
<td>12 &lt; age ≤ 25</td>
<td>.268</td>
<td>.078</td>
<td>.191</td>
<td>.709</td>
</tr>
<tr>
<td>25 &lt; age</td>
<td>.251</td>
<td>.076</td>
<td>.176</td>
<td>.698</td>
</tr>
<tr>
<td>Range among 2-digit industries</td>
<td>.067–.726</td>
<td>.022–.282</td>
<td>.045–.574</td>
<td>.368–.791</td>
</tr>
</tbody>
</table>
of the employer. Even so, it is still about 18% per quarter in the oldest employers and 13% in the largest employers.

There are two ways of measuring the importance of churning flows in worker flows. Remaining with table 1 (nonmanufacturing), the question, what proportion of all worker flows are churning flows, is answered by dividing 22.8% by 32.3% to get 0.706 (ratio of the means). A second approach, coincidentally generating a very similar figure, takes the mean of the ratio (CFR/WFR) over time and employers; this is reported as the fourth column of the table, at 0.704 for the whole nonmanufacturing sample. The rest of the table shows that the average over different subgroups does not vary substantially from this figure, never falling below 0.640.

Turning to manufacturing industries in table 2, the data reveal lower but still considerable churning flows. A much lower worker flow rate of 19.4% is made up of a marginally lower job reallocation rate of 7.4% and a far lower churning rate of 12.1%. Churning flows account for 62.4% of all worker flows, and the ratio (CFR/WFR) averages 61.9%. Again, churning flows are important throughout the age and size distribution. Our figure of 37.6% of worker flows accounted for by job flows

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12 A comparison here can be made to Anderson and Meyer’s (1994) finding that 31% of total worker flows are due to (permanent) job flow; this figure relates to all industries, which is dominated by nonmanufacturing.

13 This is a little lower than Davis et al.’s (1996) quarterly rate of 10.6%, but because of our exclusion of matches shorter than a quarter this is expected.
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in manufacturing can be compared to the estimate of 35%-56% constructed by Davis and Haltiwanger (1992), using their employer data plus data from the CPS. In their sample, Anderson and Meyer (1994) find 24% of worker flows in manufacturing to arise from permanent job flows.

The frequency distribution of the ratio (CFR/WFR) is shown in figure 1. The source of the polymodal shape is explained below when we examine the dynamic evolution of churning and job flows. Clearly, for most employers for most of the time, job reallocation flows are a minor factor in their worker flows.

There are also substantial differences across industries in both the levels

![Figure 1: Distribution of (CFR/WFR)](image-url)
Table 3
Duration of Job Matches

<table>
<thead>
<tr>
<th></th>
<th>% Workers Employed in 1985:3 Still Employed at the Same Establishment (Reporting Unit) by the Year Shown</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Nonmanufacturing (%)</td>
</tr>
<tr>
<td>1986:3</td>
<td>72.1</td>
</tr>
<tr>
<td>1987:3</td>
<td>62.2</td>
</tr>
<tr>
<td>1988:3</td>
<td>59.8</td>
</tr>
<tr>
<td>1990:3</td>
<td>47.3</td>
</tr>
<tr>
<td>1994:3</td>
<td>42.1</td>
</tr>
</tbody>
</table>

NOTE.—This calculation is performed over all reporting units surviving to the date shown.

of labor reallocation and the importance of churning in the process of reallocation. Tables 1 and 2 report ranges among two-digit industries for the flows and for the CFR/WFR ratio. These ranges point to a considerable amount of idiosyncracy at the industry level, particularly in nonmanufacturing where the rate of worker reallocation is as high as 73%, and the importance of churning in that worker reallocation ranges from 37% to 79%. This suggests that the factors contributing to match reevaluation vary across industry.

This level of churning does not necessarily imply that most workers are churned. High worker flow rates can be reconciled with the findings of “lifetime” jobs (Hall 1982; Ureta 1992) given sufficient heterogeneity in separation rates across workers. We address the issue of whether churning is confined to a fringe of high turnover positions by taking all workers employed in 1985:3 and asking how many are still employed by the same employer after 1, 2, 3, 5, and 9 years. We do not know how long these people had already been employed by 1985:3, so we can only put a lower bound on the tenure distribution. Table 3 presents the results of this exercise. It shows that there does indeed appear to be a stable core of positions and workers: 42% of workers were still employed by the same employer after 9 years in nonmanufacturing, 32% in manufacturing, despite the huge worker flow rates recorded above. The 3-year rate also corroborates the findings by Anderson and Meyer that over 59% of workers only have one job during the 3-year period they analyze.

This section has shown churning flows to be high and pervasive across

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14 Details on differences in job and worker flow rates by industry can be found in Lane, Stevens, and Burgess (1996).
15 We thank a referee for this idea.
16 It might be expected that the retention rate would be higher in manufacturing, but over this period, employment in manufacturing in Maryland fell, while employment in nonmanufacturing rose.
all age and size classes. Though there are variations in the churning rate across industry, there are no industries in which churning is negligible. Churning flows account for most worker flows in most industries. We have further shown that this high churning coexists alongside a stable core of job positions.

2. Time Series

We described the role of the business cycle trough as potentially being a cleansing period. In other words, downturns in the economy may be a chance for employers to shed their (now known-to-be) least productive workers, reducing the need for current churning; upturns in the economy increase the chance of errors in hiring and hence subsequent increases in churning. We examine the time-series evidence to determine whether this is indeed the case. Figure 2 presents the aggregated flows over time for the aggregate (Maryland) nonmanufacturing and manufacturing sectors. In the nonmanufacturing series, there is some evidence of seasonality in CFR (and therefore in WFR), and a negative correlation between CFR and JRR (the correlation is \(-0.292\)). Neither of these are true in manufacturing (the correlation is 0.105). In both sectors, CFR tends to be somewhat lower at the end of the period. We establish the cyclicality of these aggregate flows more formally by regressing them on the Maryland unemployment rate (lagged 1 quarter), seasonal dummies, and the real interest rate. These show that aggregate churning flows are procyclical and job reallocation rates are countercyclical.\(^{17}\) The former effect is stronger indicating that the aggregate worker reallocation rate is procyclical. In other words, this suggests that the behavior underlying the two processes are rather different. We return to this in Section IIIB when we study the dynamic interrelationship of the two flows at employer level.

3. Employer-Level Heterogeneity

We now characterize the nature of the employer-level heterogeneity in churning flows underlying the cross-sectional distribution described

\[ JRR_t = 0.101^* + 0.019^*U_{t-1} + 0.003TB_t + 0.015Q2 - 0.008Q3 + 0.011Q4 \quad [R^2 = 0.43] \]

and

\[ CFR_t = 0.330^* - 0.030^*U_{t-1} + 0.003TB_t + 0.034^*Q2 - 0.061^*Q3 + 0.011Q4 \quad [R^2 = 0.86], \]

where \(U\) is the Maryland unemployment rate, \(TB\) is the 3-month Treasury-bill rate minus the change in the consumer price index (CPI), \(Q_j\) are seasonal dummies, and both regressions have 36 observations. The starred coefficients are significant at the 5% level. Anderson and Meyer (1994) find similar results on cyclicity for their breakdown of worker flows.
above. We think of churning flows as arising from the process of job match reevaluation; therefore, the relative importance of employer-specific fixed effects reveals the extent of persistent differences in environment and match reevaluation policies adopted by employers. If there are consistently high-churning employers and consistently low-churning employers coexisting within narrowly defined industries, this is suggestive of different equilibrium personnel policies; conversely, the lack of employer-fixed effects would indicate that the need for churning was a chance event spread randomly across employers.
In order to capture this, we can think of the total variation in each flow, JFR, JRR, CFR, and WFR, as being split up into aggregate time effects, industry-specific effects, and employer-specific (idiosyncratic) effects. The employer effect in turn can be split up into the employer mean (the fixed effect) and variation around that. Much has been made of the overwhelming importance of the idiosyncratic component in job reallocation. Here we show that a similar result is true for worker reallocation, both in total and looking specifically at the churning flows. To do this we regress each of the flow rates on seasonal dummies and combinations of time dummies, three-digit industry dummies, and employer dummies (fixed effects), and compare the proportion of variance explained.

The results are in table 4, which simply presents the $R^2$s from these regressions, separately for nonmanufacturing and manufacturing. We confirm the findings of Leonard (1987) and Davis and Haltiwanger (1990) who demonstrate the importance of the idiosyncratic component for gross job flows. Even in a relatively small state such as Maryland, with time dummies and employer-fixed effects, less than 10% of the variation in JFR is explained. The $R^2$s are a little higher in the JRR regressions, indicating the greater importance of industry and employer effects in explaining job reallocation. For churning flows, the numbers are twice as high: idiosyncratic factors still account for about 50% of the variation in nonmanufacturing (60% in manufacturing), but there are more influential systematic factors. The most important single factor is the employer-fixed effect. Comparing nonmanufacturing and manufacturing, the figures for JFR and JRR are similar, but in CFR the $R^2$s are higher in the former. The implication of this is that time-invariant employer-level factors are more important for churning flows than for job reallocation flows.

**Table 4**

Components of Job, Worker, and Churning Flows

<table>
<thead>
<tr>
<th></th>
<th>Job Reallocation Rate</th>
<th>Worker Flow Rate</th>
<th>Job Flow Rate</th>
<th>Churning Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nonmanufacturing:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employer</td>
<td>.28</td>
<td>.54</td>
<td>.09</td>
<td>.52</td>
</tr>
<tr>
<td>Industry</td>
<td>.05</td>
<td>.14</td>
<td>.002</td>
<td>.13</td>
</tr>
<tr>
<td>Employer, time</td>
<td>.28</td>
<td>.56</td>
<td>.10</td>
<td>.54</td>
</tr>
<tr>
<td>Industry, time</td>
<td>.05</td>
<td>.16</td>
<td>.01</td>
<td>.15</td>
</tr>
<tr>
<td>Time</td>
<td>.006</td>
<td>.02</td>
<td>.009</td>
<td>.02</td>
</tr>
<tr>
<td>Manufacturing:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employer</td>
<td>.24</td>
<td>.39</td>
<td>.11</td>
<td>.37</td>
</tr>
<tr>
<td>Industry</td>
<td>.03</td>
<td>.05</td>
<td>.006</td>
<td>.04</td>
</tr>
<tr>
<td>Employer, time</td>
<td>.25</td>
<td>.41</td>
<td>.12</td>
<td>.40</td>
</tr>
<tr>
<td>Industry, time</td>
<td>.04</td>
<td>.07</td>
<td>.01</td>
<td>.07</td>
</tr>
<tr>
<td>Time</td>
<td>.007</td>
<td>.02</td>
<td>.008</td>
<td>.03</td>
</tr>
</tbody>
</table>

*Note.*—These are $R^2$s from regressing the variable named at the top of the column on seasonal dummies and the dummies named in the row. For nonmanufacturing, there are 63,873 employers; 929,912 observations in each regression. For manufacturing, there are 3,648 employers; 62,711 observations in each regression.
Figure 3 illustrates the key result of table 4 in a most striking way. Define the idiosyncratic component of churning as the churning rate of employer $i$ at time $t$ minus the sector (three-digit industry) churning rate at time $t$. The idiosyncratic job flow rate is defined analogously. We rank all employers by their idiosyncratic churning rate in 1985:3 and assign them into quintiles on the basis of this. We then calculate the average idiosyncratic churning rate of each quintile in each following time period. We then repeat this procedure based on the idiosyncratic job flow rate.

If there were no employer-level persistence in these flows, there would be little long-term pattern in the figures. This is indeed the case for job
reallocation. But the figure demonstrates that the reverse is true for idiosyncratic churning flows. Employers who were ranked in the highest quintile in 1985:3 still have high churning in each subsequent period. The stability of relative idiosyncratic churning is complete: the lines do not cross once during the entire time. The absolute level of idiosyncratic churning is also remarkably constant among the lower four quintiles. The top quintile does regress to the mean, but note that this is over a 9-year period and this quintile still shows the highest idiosyncratic churning; the comparison with the picture for idiosyncratic job flows is striking.

Bearing in mind that the data underlying this picture have had three-digit industry average effects removed, this shows a remarkable persistence in employer-level churning. Regardless of industry affiliation, there are high-churning employers and low-churning employers. These differences presumably arise from enduring features of an employer's personnel policies, arising in turn from the fundamentals of its technology, skills, and cost structure. The efficiency wage literature considers the case of employers setting wages to discourage costly excess turnover (churning) and minimise total costs. In a set of employers with differing technologies (including monitoring costs), there may coexist a variety of optimal policies: a high wage-low churning strategy or a low wage-high churning strategy. Note that the argument is not that high-wage employers should have low worker flows, because some worker flows are required for the employer to reach its desired size, but that excess worker turnover should be low.

We can explore this issue since we have average earnings information for the employers. Specifically, each employer reports earnings for each worker each quarter. We take the mean of these for full-quarter workers as our measure of the employer's average earnings, and the difference between this and the three-digit industry average as the measure of idiosyncratic average earnings. We regress idiosyncratic churning (defined above) on the employer's idiosyncratic average earnings, employer size, and seasonal dummies. The results are in table 5. We do this with churning dated contemporaneously with the wage, and with the wage lagged 1 period behind churning. Table 5 consistently shows a negative correlation between idiosyncratic churning and the wage, controlling for size. This is repeated across all three dates and whether the wage is lagged or not. The results suggest that there is some systematic component to churning flows, which is correlated with the employer's wage/personnel policy. It is also clear that differences in wages explain little of the differences in churning since the $R^2$s are quite low.

---

18 This is not to say that there are no industry differences, quite the reverse. An almost identical graph is created (but not reported here) if the unit of observation is the three-digit industry. This is consistent with industry differences in hiring and training costs relative to wage costs.
### Table 5
The Relationship between Idiosyncratic Churning and Idiosyncratic Wages

<table>
<thead>
<tr>
<th>Earnings Dated</th>
<th>Contemporaneous</th>
<th>Lagged Once</th>
<th>Contemporaneous</th>
<th>Lagged Once</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>.027</td>
<td>.0099</td>
<td>-.003</td>
<td>-.012</td>
</tr>
<tr>
<td>(76.54)</td>
<td>(29.44)</td>
<td>(4.71)</td>
<td>(18.96)</td>
<td></td>
</tr>
<tr>
<td>Idiosyncratic</td>
<td>-.08</td>
<td>-.1</td>
<td>-.08</td>
<td>-1</td>
</tr>
<tr>
<td>Earnings (+10000)</td>
<td>(87.70)</td>
<td>(123.63)</td>
<td>(88.43)</td>
<td>(121.34)</td>
</tr>
<tr>
<td>Establishment size</td>
<td>-.0013</td>
<td>-.0012</td>
<td>-.0012</td>
<td>-.001</td>
</tr>
<tr>
<td>(4.28)</td>
<td>(3.69)</td>
<td>(4.24)</td>
<td>(3.75)</td>
<td></td>
</tr>
<tr>
<td>Second quarter</td>
<td>..</td>
<td>.046</td>
<td>.033</td>
<td></td>
</tr>
<tr>
<td>Third quarter</td>
<td>..</td>
<td>.064</td>
<td>.054</td>
<td></td>
</tr>
<tr>
<td>Fourth quarter</td>
<td>..</td>
<td>.011</td>
<td>.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>.007</td>
<td>.02</td>
<td>.01</td>
<td>.02</td>
</tr>
</tbody>
</table>

**Note.**—Unit of observation is an employer-quarter. There are 1,036,172 observations; t-statistics in parentheses.

This section has established that high and low churning flows are persistent features of some employers’ personnel policies. Since most of our employers are long-lived, this suggests to us that there are different and sustainable (i.e., successful) personnel/recruitment policies available. That is, churning is an equilibrium phenomenon. This view is strengthened by the correlation between excess churning and idiosyncratic wages. Some of the modeling issues were noted above in Section II. There appear to be a number of interesting questions to be asked in this area.

### B. Dynamic Relationship of Churning and Job Flows

We now turn to analyze the dynamic determination of churning flows, the relationship between worker and job flows over time at the employer level. Clearly many factors affect job flows, most obviously, product demand and business cycle shocks. However, at the aggregate level, Davis and Haltiwanger (1990) show that gross job destruction is more sensitive to the cycle than is gross job creation, implying that gross job reallocation is countercyclical.19 Similarly, as we have discussed, many factors affect worker flows, but we have also demonstrated that gross worker flows tend to be procyclical. If it is more profitable to reallocate jobs in a recession, it seems more profitable to reallocate workers in a boom. The evolution of churning flows (the difference between worker and job flows) is the link between the two and may give us some further clues as to the determination of the reallocation of

19 A thorough survey of the international evidence is contained in Organization for Economic Cooperation and Development (1994).
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labor. Using our dataset, we can explore this link at the level of the employer. We argued above that positive job flows will likely raise subsequent churning flows. The appropriate theoretical model to consider the effect of churning flows on job flows is less clear, but efficiency wage ideas would suggest that high churning would be deleterious to the employer in the presence of high turnover costs.

A useful first step to establish an empirical link between job and churning flows is a graphical investigation. We plot an employer's job flow rate against its worker flow rate in a particular quarter. Since worker flows are never less than job flows, all points will lie on or above a pair of 45 degree lines. The vertical distance between a point and the diagonal is the churning flow rate. What might we expect to see? If churning is greatest when employers are experiencing rapid growth or decline, we would expect the mass of points to lie around lines steeper than 45 degrees; if churning occurs when job flows are lower, we would expect a flatter plot. There is no reason why it should be symmetrical about JFR = 0.

Figure 4 shows a plot of all the data points we have, that is, all dates for all employers. This picture therefore combines the time-series pattern for an employer with the distribution of employers across this space. The picture shows that higher churning flow rates tend to be associated with lower absolute job flow rates. For high absolute values of job flow rates, almost all worker flows are accounted for by job flows. Below that, where the bulk of the data points lie, churning flows on average dominate worker flows. This picture explains the shape of the frequency plot of churning flows in figure 1: some employers with high absolute values of job flow rates have very low CFR, whereas the main mass of employers with lower absolute values of job flow rates have much higher CFR.
However, as noted, this combines the time-series variation employer-by-employer with the cross-section distribution of employers. To isolate the former, in figure 5 we plot the \{WFR, JFR\} sequence separately for a selection of employers. As might be expected, there is a great variety of shapes. For example, for employer 1 ("Emp. 1"), there are some "flares" as both JFR and WFR increase dramatically together and then fall back together. This case shows WFR being driven by JFR: the employer wants to expand and so hires to achieve that. These are flows, so once the new desired employment level is reached, the flows fall back to previous levels. This is the sort of pattern that might be expected if churning flows were just "froth" on top of the driving JFR. But a quite different sort of picture is evident for employer 2. Here there is no obvious pattern, with negative comovements as likely as positive. Examining a number of such pictures, it is clear that there are many episodes for many employers when JFR and WFR are negatively correlated, or when the JFR changes with no effect on WFR, or vice versa.

Reporting impressions from our viewing of several such plots, out of potentially many thousands of employer plots, is not very scientific. As a preliminary step we look at some simple correlations of churning and job flows across different time spans in table 6.\textsuperscript{20} Clearly there is positive autocorrelation in churning rates, displaying persistence in response to shocks; the negative autocorrelation in job flow rates suggests a different adjustment process. The cross correlations are significant at almost all lag lengths. In particular, job flows and churning flows are contemporane-

\textsuperscript{20} These are the fundamental components; their sum gives worker flows, which are plotted in figs. 4 and 5.
Table 6
Dynamic Correlations of Job Flow Rates and Churning Flow Rates

<table>
<thead>
<tr>
<th>Job Flow Rates</th>
<th>Churning Flow Rates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>Coefficient</td>
</tr>
<tr>
<td>JFR(t - 1)</td>
<td>.078</td>
</tr>
<tr>
<td>JFR(t - 2)</td>
<td>.234</td>
</tr>
<tr>
<td>JFR(t - 3)</td>
<td>.061</td>
</tr>
<tr>
<td>JFR(t - 4)</td>
<td>.210</td>
</tr>
<tr>
<td>JFR(t - 5)</td>
<td>.050</td>
</tr>
<tr>
<td>JFR(t - 6)</td>
<td>.120</td>
</tr>
<tr>
<td>CFR(t)</td>
<td>.158</td>
</tr>
<tr>
<td>CFR(t - 1)</td>
<td>.069</td>
</tr>
<tr>
<td>CFR(t - 2)</td>
<td>.011*</td>
</tr>
<tr>
<td>CFR(t - 3)</td>
<td>.053</td>
</tr>
<tr>
<td>CFR(t - 4)</td>
<td>.020</td>
</tr>
<tr>
<td>CFR(t - 5)</td>
<td>.057</td>
</tr>
<tr>
<td>CFR(t - 6)</td>
<td>.016</td>
</tr>
</tbody>
</table>

Note.—JFR = job flow rates; CFR = churning flow rates. Each coefficient is derived from running a regression of the variable at the top of the column on a set of establishment-specific constants, and the one variable in the relevant row only; e.g., the top left coefficient is $b$ in $\text{JFR}_t = a + b \cdot \text{JFR}_{t-1} + \epsilon_t$. All of the coefficients are significant at the 5% level except the starred ones.

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...Previously positively correlated, suggesting that employment expansions are associated with increased churning, contractions with decreased churning. This is consistent with the cleansing idea that we posited earlier. The link between prior churning and current job flows, and prior job flows and current churning, is less obvious, and we thus turn to a more systematic approach to characterize this dynamic relationship.

In order to do this, we specify a VAR on the panel of employers. This enables us to examine two phenomena: the nature of causality between these series and the magnitude of the effects. We are fortunate in that we have a rather long time dimension for panel data: in our full sample with a total of 66,534 employers who appear in at least 1 quarter, 23,069 employers had runs of at least 20 periods, and 13,714 had runs of at least 30 periods. Consequently, we were able to allow for the maximum heterogeneity by estimating a separate VAR for each employer, although for degrees of freedom reasons we first included employers with at least 10 observations, and then reran the regressions with only employers with at least 20 observations. Each VAR was of the following form:

21 The issues involved in the estimation of dynamic models using panel data have been discussed by Anderson and Hsiao (1982) and Arrelano and Bond (1991), and VARs on panels have been discussed by Holtz-Eakin, Newey, and Rosen (1988).
\[
CFR_{it} = \sum_{s=1}^{m} \alpha_{1s} CFR_{i,t-s} + \sum_{s=1}^{m} \alpha_{2is} JFR_{i,t-s} + \nu_{1it}
\]

and

\[
JFR_{it} = \sum_{s=1}^{m} \beta_{1s} CFR_{i,t-s} + \sum_{s=1}^{m} \beta_{2is} JFR_{i,t-s} + \nu_{2it}
\]

where \(i\) indexes employers, and \(t\) indexes time, and the \(\nu_{it}\) are employer-specific error terms. The lag length chosen was 4.

The results on Granger causality tests show significant interactions between these two series for many employers. In nonmanufacturing, at the 5% significance level, job flow rates Granger cause churning flow rates in 23% of all employers, and churning flow rates Granger cause job flow rates in 20% of all employers (these are generally different employers). In manufacturing, the figures are 23% and 21%, respectively. We discuss these results further below after reporting the general direction of these effects.

The time-series degrees of freedom in these regressions can be as low as 6 with a maximum of only 40. Thus, we present some results on the distribution of the point estimates even though only some are estimated precisely enough to achieve significance at conventional levels. In table 7 we report the quartiles and the median of the distribution of the long-run elasticities derived from the estimation for each employer: for CFR,

\begin{table}[h]
\centering
\caption{The Distribution of Long-Run Elasticities for Job Flow and Churning Flow Rates}
\begin{tabular}{|l|c|c|c|c|}
\hline
 & \multicolumn{2}{|c|}{Job Flow Rate} & \multicolumn{2}{|c|}{Churning Rate} \\
\hline
Dependent Variable & (1) & (2) & (1) & (2) \\
\hline
Nonmanufacturing: & & & & \\
Lower quartile & -1.01 & -1.11 & -.319 & -.162 \\
Median & -.264 & -.410 & .117 & .200 \\
Upper quartile & .221 & .146 & .540 & .531 \\
No. of employers & 34,311 & 21,756 & 34,311 & 21,756 \\
\hline
Manufacturing: & & & & \\
Lower quartile & -.766 & -.919 & -.353 & -.074 \\
Median & -.084 & -.254 & .147 & .276 \\
Upper quartile & .264 & .251 & .591 & .586 \\
No. of employers & 2,375 & 1,313 & 2,375 & 1,313 \\
\hline
\end{tabular}
\end{table}

\textit{Note.}—The numbers are the long run elasticities as defined in the text for the effect on the dependent variable of the other variable. The numbers reported are the quartiles from that distribution of elasticities (1) VAR with 4 lags and in existence more than 10 quarters and (2) VAR with 4 lags and in existence for more than 20 quarters.
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$\alpha_2(1)/[1 - \alpha_1(1)]$ and for JFR, $\beta_1(1)/[1 - \beta_2(1)]$, where $\alpha_2(1)$ indicates the sum of the $\alpha_{2i}$ values.\textsuperscript{22} The results suggest that in most employers, lagged job flows positively affect churning flows.

Further analysis of these results by size, age, and industry are reported in table 8. The distribution of the coefficients is rather stable in each table. For most employers, high churning flows follow high job flows, and increased churning leads to employment contraction, regardless of age or industry. There are some interesting patterns within this overall picture, however. The first is that the order of magnitude of the elasticities is, by and large, the same across industries but changes quite markedly across age categories. The negative effect of high churning on job flows appears to be greater for the older rather than the younger employer; the same is true for the effect of job flows on churning. The second is the different patterns by size class: job flows are positively related with churning flows for a much higher proportion of large than for small employers, and the negative effect of churning flows on job flows is bigger for small employers than for large employers.

How is this evidence to be interpreted? The relationship between current churning flows and lagged job flows is as we expected. It supports the idea that when employers have recently expanded, there is a group of workers with uncertain match value. As the true value is revealed, churning increases. Conversely, if employment has fallen, it is likely that those with the lowest match values will have left, reducing the need for further churning.

Interestingly, though bearing in mind the caveats above, the results also suggest that in most employers in all industries, lagged churning flows are negatively associated with job flows; since these are employer-by-employer time-series regressions, the variation that is captured here is all time series. This new result is more consistent with a costly turnover/efficiency wage view of the labor market than a view that employers improve labor force quality prior to expansions. The relationship may not be causal: it could be that workers perceive that the employer will shortly decline and quit. Although this story initially seems plausible, if the decline was expected by workers it seems reasonable to assume it would be expected by managers, and they might take advantage of the natural wastage to reduce employment in a relatively costless way. In fact, churning flows are by definition replaced quits, so such a story needs to explain why new workers are hired. A causal story is the efficiency wage argument that excess worker turnover is costly and damaging to the employer. This would be consistent with the greater effect observed for small employers than for large.

\textsuperscript{22} In view of the heterogeneity of the coefficients reported, we did not reestimate imposing the same coefficients across cross-section units.
Table 8
Long Run Elasticities by Employer Characteristics

<table>
<thead>
<tr>
<th>Size Class</th>
<th>Job Flow Rate</th>
<th>Churning Flow Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Less than 50</td>
<td>50–99</td>
</tr>
<tr>
<td>Lower quartile</td>
<td>-0.972</td>
<td>-0.861</td>
</tr>
<tr>
<td>Median</td>
<td>-0.274</td>
<td>-0.119</td>
</tr>
<tr>
<td>Upper quartile</td>
<td>0.158</td>
<td>0.466</td>
</tr>
<tr>
<td>No. of employers</td>
<td>6,622</td>
<td>2,483</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Age Class</th>
<th>Job Flow Rate</th>
<th>Churning Flow Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Under 5 Years</td>
<td>5–12 Years</td>
</tr>
<tr>
<td>Lower quartile</td>
<td>-0.75</td>
<td>-0.844</td>
</tr>
<tr>
<td>Median</td>
<td>-0.006</td>
<td>-0.071</td>
</tr>
<tr>
<td>Upper quartile</td>
<td>0.872</td>
<td>0.446</td>
</tr>
<tr>
<td>No. of employers</td>
<td>239</td>
<td>2,417</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Industry</th>
<th>Agriculture, Mining, Construction</th>
<th>Manufacturing</th>
<th>Transportation, Communication, Utilities</th>
<th>Wholesale</th>
<th>Retail</th>
<th>Finance, Insurance, Real Estate</th>
<th>Professional Services</th>
<th>Other Services</th>
<th>Government</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job flow rate:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower quartile</td>
<td>-0.759</td>
<td>-0.779</td>
<td>-0.831</td>
<td>-0.862</td>
<td>-1.01</td>
<td>-0.848</td>
<td>-0.909</td>
<td>-0.909</td>
<td>-1.016</td>
</tr>
<tr>
<td>Median</td>
<td>-0.109</td>
<td>-0.129</td>
<td>-0.086</td>
<td>-0.226</td>
<td>-0.300</td>
<td>-0.122</td>
<td>-0.218</td>
<td>-0.172</td>
<td>-0.26</td>
</tr>
<tr>
<td>Upper quartile</td>
<td>0.316</td>
<td>0.314</td>
<td>0.356</td>
<td>0.297</td>
<td>0.219</td>
<td>0.321</td>
<td>0.272</td>
<td>0.323</td>
<td>0.364</td>
</tr>
<tr>
<td>No. of employers</td>
<td>1,626</td>
<td>1,092</td>
<td>496</td>
<td>1,095</td>
<td>2,388</td>
<td>771</td>
<td>1,255</td>
<td>1,995</td>
<td>408</td>
</tr>
<tr>
<td>Churning flow rate:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower quartile</td>
<td>-0.324</td>
<td>-0.165</td>
<td>-0.267</td>
<td>-0.191</td>
<td>-0.280</td>
<td>-0.119</td>
<td>-0.177</td>
<td>-0.287</td>
<td>-0.065</td>
</tr>
<tr>
<td>Median</td>
<td>0.281</td>
<td>0.291</td>
<td>0.204</td>
<td>0.279</td>
<td>0.249</td>
<td>0.303</td>
<td>0.278</td>
<td>0.243</td>
<td>0.323</td>
</tr>
<tr>
<td>Upper quartile</td>
<td>0.723</td>
<td>0.683</td>
<td>0.591</td>
<td>0.649</td>
<td>0.679</td>
<td>0.699</td>
<td>0.649</td>
<td>0.678</td>
<td>0.640</td>
</tr>
<tr>
<td>No. of employers</td>
<td>1,626</td>
<td>1,092</td>
<td>496</td>
<td>1,095</td>
<td>2,388</td>
<td>771</td>
<td>1,255</td>
<td>1,995</td>
<td>408</td>
</tr>
</tbody>
</table>

Note.—The numbers are the long run elasticities as defined in the text for the effect on the dependent variable of the other variable. The numbers reported are the quartiles from that distribution of elasticities. VAR with 4 lags; more than 20 employees and in existence more than 10 quarters.
A natural follow-up question is why the employer did not choose the optimum wage/turnover policy. The optimum policy would imply that time-series variation in churning should already be accounted for and be orthogonal to employment growth. It may be that the employer faces constraints on its choice of compensation or personnel policies, or that churning flows develop in an unforeseen manner quicker than the employer can change policy. These seem to us to be questions worth pursuing further.

IV. Conclusions

The reallocation of labor involves both the reallocation of workers amongst a fixed set of jobs and the reallocation of jobs. Although we reiterate the note of caution (see Sec. IIC above) concerning the interpretation of the term “churning flows,” we believe the dataset yields some interesting results. Davis and Haltiwanger (1990) and others have demonstrated the considerable employer heterogeneity underlying job reallocation; in this article we have shown considerable match heterogeneity over and above employer heterogeneity. Using an employer-level panel dataset, we are able to separate these out over time, employer by employer. We confirm recent findings regarding the size of gross job flows and the importance of the idiosyncratic component. More importantly, we provide new evidence on the nature of churning flows and their relationship to job flows. Briefly, we summarize our main results here.

The difference between labor reallocation and job reallocation is indicated by the magnitude of the churning flows.23 In nonmanufacturing, the quarterly churning rate is 19%, and it is 11% in manufacturing. While the rate declines with size and age of the employer, it remains around 10% in the oldest and biggest employers. Furthermore, churning flows dominate job reallocation as the source of worker reallocation. This is true in two senses: churning flows account for over 70% of worker flows in nonmanufacturing (46% in manufacturing) and the ratio of churning flows to worker flows averages over 60% across employers and time. This suggests that for most employers most of the time, most of the flows they have to deal with are churning flows. There are high churning flows throughout the labor market. There are no industries in which churning flows are unimportant. High levels of worker flows are characteristic of some employers and industries, and these effects are persistent.

Labor reallocation and job reallocation appear to be characterized by different processes: a much higher proportion of the variation in churning flows than job flows is explained by employer-fixed effects. The difference in the importance of employer effects between job flows and churning flows is striking.

23 Again recall that our definition of churning includes personnel changes arising from the employer changing the skill mix of the workforce.
The dynamic relationship between worker flows, churning flows, and job flows appears to be quite complex. Aggregate labor reallocation is procyclical and aggregate job reallocation is countercyclical. We investigate these dynamics at the employer level. We find that churning flows depend positively on recent job flows. This fits well with the idea that churning arises as recently made matches are reevaluated and some are terminated. We show that an employer’s employment growth depends negatively on its recent churning flows. There does not appear to be a good explanation for this phenomenon, and we believe it merits further attention.

Turning to the broader picture, these findings have a number of implications. First, models of labor reallocation must take account of the substantial churning flows. These are clearly important in their own right but also appear to have an effect on job flows (employment growth). This finding introduces a whole new range of issues into the job creation and destruction literature and, indeed, the labor demand literature. Second, the sheer magnitude of churning flows suggests that further research is required on the applicability of models based on employers paying high wages to (successfully) avoid high worker turnover. Finally, the importance of churning flows suggests that these must be taken into account in employment adjustment cost functions: most of the worker flows that employers have to cope with do not change the size of the employer.

Appendix

Data

I. Data Structure

The data used in this article were provided to the authors for this research through an interagency data sharing agreement between the Jacob France Center at the University of Baltimore and Maryland’s Department of Labor, Licensing and Regulation. Maryland’s unemployment insurance law stipulates that “the Secretary and Board of Appeals may not publish or allow public inspection of information obtained under this section in any manner that reveals the identity of the employer except to public employees in the performance of their public duties” (Maryland Annotated Code, Labor and Employment, article 8-625(c)).

The information subject to the confidentiality provision includes data collected from covered employing units using a quarterly unemployment insurance contribution and employment packet. The definition of an employing unit is “an employer that has at least one employee engaged in covered employment for at least part of a day.” Covered employment “means work that an individual performs for an employing unit that is the basis for benefits.”

The instructions on the employment report advise reporting employers that the following types of employees are exempt from coverage: (1) sole proprietor or partner, (2) parents, spouses, and children under 21 years of age of the sole proprietor, (3) an individual who is enrolled in a full-time educational program that combines academic instruction with work ex-
Job Flows, Worker Flows, and Churning

experience, (4) independent contractors who satisfy three conjunctive tests that are defined in the instructions, and (5) members of a limited liability company. Specific exemptions defined in the unemployment insurance law itself include some agricultural labor, some employment by charitable, educational, not-for-profit, and religious organizations, commission (only) sales, domestic employment paying less than $1,000 in cash wages during the reference quarter, and employment by the federal government or by a foreign government.

More than 90% of reporting employing units are single-establishment entities, which means that colloquial terms such as employer, business, or firm can be substituted for the unfamiliar concept of an employing unit. Transfer of ownership of such an entity results in the assignment of a new unemployment insurance tax account number to the employing unit. This number is the identifier that is used to define employing unit births and deaths and to establish the vintage, or date-of_birth, of the employing unit. The employment size-class designation for these employing units is also unambiguous. The remaining relatively small number of multiestablishment employing units are concentrated in the retail trade and selected services sectors. Some clusters of smaller employers within a multiestablishment employing unit are included in the larger employment size-classes with truly large single-establishment employing units. The Office of Labor Market Analysis and Information in Maryland's Department of Labor, Licensing, and Regulation uses a Multiple Worksite Report to obtain establishment-specific employment level and total payroll information from multiestablishment employing units whose identity is known, but this step does not identify the individual employees by worksite. The standard industrial classification (SIC) code for each employing unit is updated over a 3-year cycle, using a Bureau of Labor Statistics form, which subjects access to the SIC code to different confidentiality provisions than the other data elements that are covered by the state unemployment compensation law only.

Issues regarding the differences between firms and employers and the consequences of firm changes in the employer identification number are clearly addressed in Anderson and Meyer (1994) and also in Lane, Isaac, and Stevens (1996). The data are certainly not dominated by many takeovers and mergers: for example, in 1992 there were 1,600 successor firms out of a total of around 100,000 firms.

Errors that might arise from late reporting are minimized by acquiring each quarter of Maryland data twice: when it first becomes available 3 months after the end of the reference quarter and then again 2 quarters later. Nonreporting and erroneous reporting of individual employee's affiliation do affect the estimates that are reported here. However, these administrative records are used in the day-to-day management of the state's unemployment compensation program. This results in a high rate of compliance, as is the case in any mandatory reporting situation that involves recurring and unpredictable accessing of the records for eligibility and payment determination purposes. Late reporting occurs because of the quarterly timing of
required submission. This does not affect the archival records because they are routinely updated to reflect such cases.

The interagency data sharing agreement between the Jacob France Center and Maryland's Department of Labor, Licensing, and Regulation requires prior written authorization to prepare and release research results based on the use of the confidential records maintained by the Center. Readers who desire access to the data used in this article should contact David Stevens for further information about the criteria used by the Department to decide whether data will be released for a particular research purpose.

II. Construction of Dataset

We are primarily interested in this article in looking at employment spells that exist for at least a quarter. We therefore define people as being employed for a full quarter by making quarter-to-quarter matches of employer/employee pairs for 3 consecutive quarters. We assume that a worker who shows up as working for the same employer for 3 consecutive quarters is employed for the entire middle quarter. We define hires as people who were not with the establishment in the preceding quarter (in the above definition) but who were there in the current quarter and exit analogously (this requires 4 quarters of data). We only included employers who reported employment of more than 5 full quarter employees in the quarter. We eliminated the observation of the quarter of birth and death from the sample.

III. Representativeness

Appendix table A1 compares the industrial distribution of employment in Maryland to the nation's industry mix of employment in 1990 and as projected by the Bureau of Labor Statistics for the year 2005. Maryland’s employment mix is more like that projected for the turn of the century, which makes the analysis reported here of particular interest from a policy importance and replication standpoint. In particular, it is evident that the move from manufacturing to nonmanufacturing, which has been so marked in the 1980s, is projected to continue into the next century. This would suggest that studies that focus only on the manufacturing sector will be of less interest to policy makers than studies that provide data on every sector of the economy.

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<thead>
<tr>
<th>Table A1</th>
<th>Employment by Sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, mining, construction</td>
<td>8.1</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>16.9</td>
</tr>
<tr>
<td>Transportation, communication</td>
<td>5.2</td>
</tr>
<tr>
<td>Wholesale, retail trade</td>
<td>22.3</td>
</tr>
<tr>
<td>Finance, insurance, real estate</td>
<td>6.0</td>
</tr>
<tr>
<td>Services</td>
<td>24.5</td>
</tr>
<tr>
<td>Government</td>
<td>16.3</td>
</tr>
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</table>

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