

Looking into the Black Box: A Survey of the Matching Function

BARBARA PETRONGOLO *and* CHRISTOPHER A. PISSARIDES¹

1. Introduction

FRICTIONS HAVE MADE important inroads in modern macroeconomics. In the labor market they are used to explain the existence of unemployment and (sometimes) wage inequality. In business cycle models they are used to explain the amplification of the response of employment to aggregate shocks. In coordination-failures models they are used to justify the dependence of the strategy of one agent on that of another. In monetary models they are used to explain the existence of money.² In the majority of cases, the modeling tool used to capture the influence of frictions on equilibrium outcomes is the aggregate matching function. This paper surveys recent work

¹Petrongolo: University Carlos III, Madrid, Centre for Economic Performance, and CEPR. Pissarides: Centre for Economic Performance, London School of Economics, and CEPR. We are grateful to Alan Manning, Tony Venables, Étienne Wasmer, seminar participants at ESSLE 2000, and an anonymous referee for useful comments. Funding for this project was provided by the Centre for Economic Performance, the Economic and Social Research Council, and the Spanish Ministry of Education (Grant No PB97–0091).

²Representative references include Pissarides (2000) and Dale Mortensen and Pissarides (1999b) on the labor market; James Montgomery (1991) and Daron Acemoglu and Robert Shimer (2000) on wage inequality; Monika Merz (1985) and David Andolfatto (1986) on business cycles; Russell Cooper and Andrew John (1988) and Peter Diamond (1982a) on coordination failures; and Diamond (1984) and Nobuhiro Kiyotaki and Randall Wright (1989) on monetary exchange.

on the existence and stability of the aggregate matching function, with emphasis on microfoundations and empirical findings.

The attraction of the matching function is that it enables the modeling of frictions in otherwise conventional models, with a minimum of added complexity. Frictions derive from information imperfections about potential trading partners, heterogeneities, the absence of perfect insurance markets, slow mobility, congestion from large numbers, and other similar factors. Modeling each one of these explicitly would introduce intractable complexities in macroeconomic models. The matching function captures their effects on equilibrium outcomes in terms of a small number of variables, usually without explicit reference to the source of the friction.

Frictions also introduce monopoly rents in competitive markets, which influence behavior. The matching function has been used to study their implications for wage and price determination.³ The appendix traces the history of frictions in economic modeling, leading up to the recent generation of equilibrium models with matching frictions. It argues that although the matching function

³See, for example, Diamond (1982b) and the labor market references in the preceding footnote.

was not “discovered” by the recent vintage of models, in the sense that the idea (and sometimes functional form) were present in earlier models, it was not until the late 1970s that it explicitly appeared in equilibrium models and was given a new and far more important role in the characterization of equilibrium than had previously been the case. Influential in this respect were equilibrium models of wage and employment determination (Peter Diamond 1982a,b; Dale Mortensen 1982a,b; and Pissarides 1984, 1985).

Virtually all the work that we survey focuses on the labor market. This is partly explained by the fact that frictions are likely to be more important in the labor market than in other markets. But it also has to do with the fact that in labor markets there are data sets that can be used to estimate and test the matching function. A lot of the recent interest in the matching function stems from the realization that modern labor markets are characterized by large well-documented flows of jobs and workers between activity and inactivity.⁴ The matching of workers to new jobs is one-half of the explanation for these flows. Its outcome, in conjunction with the outcome of the process that separates workers from jobs, is often shown graphically in vacancy-unemployment space by the “Beveridge curve” (Pissarides 2000, ch. 1; Olivier Blanchard and Diamond 1989). Estimated Beveridge curves can shed light on the nature of the aggregate matching function, and we discuss some below. Most of the evidence that we discuss, however, is in

studies that estimate a matching function directly, either at the aggregate or the sectoral level.

In section 2 we discuss the main ideas behind the matching function and we give some pertinent evidence. We then take a look at the theoretical foundations of the matching function and discuss some of the more important variables that are likely to be influential in empirical work (section 3). Section 4 discusses empirical results in the context of the methods most frequently adopted in the estimation of the matching function. Section 5 deals with the conceptual and measurement issues due to search on the job and to workers’ transitions from out of the labor force to employment. Aggregation problems across time and space are discussed in section 6. The main conclusions are brought together in section 7. The appendix gives a brief historical overview of the literature on the role of labor market frictions, leading to the birth of the matching function.

2. *The Key Idea and Some Evidence*

The matching function summarizes a trading technology between agents who place advertisements, read newspapers and magazines, go to employment agencies, and mobilize local networks that eventually bring them together into productive matches. The key idea is that this complicated exchange process is summarized by a well-behaved function that gives the number of jobs formed at any moment in time in terms of the number of workers looking for jobs, the number of firms looking for workers, and a small number of other variables.

The matching function is a modeling device that occupies the same place in the macroeconomist’s tool kit as other aggregate functions, such as the production function and the demand for

⁴ See Steven Davis, John Haltiwanger, and Scott Schuh (1996) on the importance of job flows and Blanchard and Diamond (1990a) on the importance of worker flows in the United States; and Michael Burda and Charles Wyplosz (1994) and Bruno Contini, Lia Pacelli, Michelangelo Filippi, Graciela Lioni, and Riccardo Revelli (1995) on the importance of flows in Europe.

money function. Like the other aggregate functions its usefulness depends on its empirical viability and on how successful it is in capturing the key implications of the heterogeneities and frictions in macro models. In this survey we will focus on the microfoundations underlying the matching function and on its empirical success but we will not discuss its modeling effectiveness.

The simplest form of the matching function is

$$M = m(U, V), \quad (1)$$

where M is the number of jobs formed during a given time interval, U is the number of unemployed workers looking for work and V the number of vacant jobs. The matching function is assumed increasing in both its arguments and concave and usually homogeneous of degree 1. Testing for homogeneity, or constant returns to scale, has been one of the preoccupations of the empirical literature. Other restrictions usually imposed are $m(0, V) = m(U, 0) = 0$, and in discrete-time models where M is the flow of matches during an elementary period and U and V are the stocks at the beginning of the period, $m(U, V) \leq \min(U, V)$. In continuous time models, M is the instantaneous rate of job matching and U and V the instantaneous stocks of unemployment and vacancies. In the absence of frictions, $M = \min(U, V)$ in discrete-time formulations and $M \rightarrow \infty$ in continuous-time models. Under constant returns to scale, M , U , and V are usually normalized by the labor force size, and denoted by lower-case letters.

On average, an unemployed worker finds a job during a period of unit length with probability $m(U, V)/U$. Similarly, a vacant job is filled with probability $m(U, V)/V$. In a stationary environment, the inverse of each probability is the mean duration of unemployment and vacancies respectively. Of course, if

workers and jobs are heterogeneous, the transition probabilities (or hazard rates) will differ across the labor market, as will the mean durations. The aggregate matching function is a useful device for introducing heterogeneities across workers, by making the probability $m(U, V)/U$ depend on individual characteristics. This has been a theme of the empirical literature that estimates hazard functions for individual workers.

The dependence of the mean transition rates on the number of workers and firms engaged in search is an externality that has played an important role in the analysis of the efficiency of search equilibrium. The average time that it takes a firm to find a worker depends on what searching workers do before they meet the firm. Similarly, the probability that an unemployed worker finds a job depends on what hiring firms do, for example on whether they advertise or not and where they advertise. Generally, search equilibrium is inefficient because when firms and workers meet, the costs of their search, which influence the transition probabilities, are sunk. Estimated matching functions can give a measure of the extent of the externalities. If the elasticity with respect to unemployment in the matching function is η_U and the elasticity with respect to vacancies η_V (not necessarily constants), $\eta_U - 1$ measures the negative externality (congestion) caused by the unemployed on other unemployed workers, and η_V measures the positive externality (thick-market effect) caused by firms on searching workers. Similarly, η_U measures the positive externality from workers to firms, and $\eta_V - 1$ measures the negative externality by firms on each other. Higher elasticity estimates indicate less congestion and more positive externalities.

The returns to scale in the matching

function play an important role in models with endogenous search effort. If there are increasing returns to matching (in the notation above, if $\eta_U + \eta_V > 1$), as the authors of some early models assumed (Diamond 1982a; Peter Howitt and Preston McAfee 1987), there could be more than one equilibrium, because of the strong positive externalities: in one equilibrium firms and workers put more resources into search, pushing up the returns from search available to the other side, which justify the bigger inputs; in another they put less effort into search with lower returns from search, lower matching rate, and higher unemployment. Increasing returns to scale can support the high and low activity equilibria even when there are increasing marginal costs to search effort, whereas constant returns cannot (although the complementarity between the actions of firms and workers is still present).

Evidence on the key matching-function idea comes from four sources. The first one uses aggregate data on stocks of unemployment and vacancies and estimates an equilibrium relation, the Beveridge (or *UV*) curve. The second uses aggregate data on employment and unemployment flows and estimates the aggregate matching function, either for the whole economy or for a particular sector (usually manufacturing). The third uses data on local labor markets, which can be either a time-series or a panel, and estimates the matching function for each. The fourth uses data on individual transitions and estimates hazard functions for unemployed workers. We discuss each approach in some detail in subsequent sections. Here we summarize the main implications of the empirical research for the simple matching function in (1).

The Beveridge curve is an equilibrium relation that equates flows in with

flows out of unemployment. In vacancy-unemployment space it slopes downward if the outflow from unemployment is given by the matching function in (1). Estimated Beveridge curves slope downward but shift over time, especially in cases where there have been secular increases in unemployment, as in most European countries since the mid-1970s. So the matching function in (1) is not contradicted by the Beveridge-curve evidence, but this evidence is indirect; it is consistent with other mechanisms, and points to other variables that influence job matching too.

Direct estimates of the matching function give better information about the properties of (1). Table 1 summarizes the specifications adopted by aggregate studies. Most studies that estimate aggregate functions find that a log-linear approximation to (1) with constant returns to scale fits the data well, although some estimates with translog specifications find increasing returns. The estimated elasticities with respect to unemployment and vacancies vary, depending on whether the dependent variable is the outflow from unemployment, the flow from unemployment to employment, or the total number of hires. When the dependent variable is the total outflow from unemployment, the estimated elasticity on unemployment is about 0.7 and the elasticity on vacancies 0.3. Precise data on unemployment-to-employment transitions are rarely available, but when an approximation for the matching rate is used the elasticity on unemployment drops, although not by much when other flows into employment are ignored. A plausible range for the empirical elasticity on unemployment is 0.5 to 0.7, showing that perhaps the congestion effects caused by firms on each other are bigger than the ones caused by workers on each other. There are good reasons for the drop in the

TABLE 1
AGGREGATE MATCHING FUNCTION STUDIES

Author	Country and coverage	Period and frequency	Dependent variable	Job seekers
Pissarides 1986	U.K., men	1967–83 quarterly	male unempl. outflow rate	unemployed men
Blanchard and Diamond 1989, 1990b	U.S.	1968–81 monthly	all new hires	unemployed; laid-off; out of LF; STU and LTU
Layard, Nickell, and Jackman 1991	Britain	1968–88 quarterly	unempl. outflow rate	unemployed
van Ours 1991	Netherlands	1961–87 annual	vacancy outflow	unemployed
Burgess 1993	U.K., men	1968–85 quarterly	male unempl. outflow rate	male unempl. rate
Burda and Wyplosz 1994	France Germany Spain U.K.	1971–93 1968–91 1977–92 1985–93 (all monthly)	unemployment outflow	unemployed
Warren 1996	U.S. manufacturing	1969–73 monthly	all new hires	unemployed (from manuf.)
Feve and Langot 1996	France	1971–89 quarterly	—	—
Berman 1997	Israel	1978–90 monthly	referrals	unemployed
Gross 1997	Germany (West)	1972–94 quarterly	all new hires	unemployed
Gregg and Petrongolo 1997	Britain	1967–96 quarterly	unempl. outflow; vacancy outflow	unemployed
Bell 1997	France Britain Spain	1979–94 1967–85 1980–95 (all quarterly)	unempl. outflow new hires new hires	unemployed
Bleakley and Fuhrer 1997	U.S.	1979–93 monthly	hires from U	unemployed
Coles and Smith 1998	Britain	1987–95 monthly	unempl. outflow by duration	U stock U inflow
Mumford and Smith 1999	Australia	1980–91 quarterly	U outflow rate; outflow rate from out of LF	unemployed (from manuf.)
Yashiv 2000	Israel	1975–89 monthly	all new hires	unemployed

TABLE 1 (Cont.)

Author	Job vacancies	Other variables	Specification
Pissarides 1986	notified, adjusted	Time trend, mismatch, replacement ratio	linear; log-linear
Blanchard and Diamond 1989, 1990b	help-wanted index adjusted	time trend	log-linear; CES
Layard, Nickell, and Jackman 1991	notified	time trend, search intensity index	log-linear
van Ours 1991	notified, adjusted	replacement ratio, LTU/U	log-linear
Burgess 1993	—	male hires, replacement ratio, demographic variables, LTU/U	log-linear
Burda and Wyplosz 1994	notified	time trend	log-linear
Warren 1996	help-wanted index (in manuf.)	—	translog
Feve and Langot 1996	notified	a general-equilibrium small open economy model is estimated, in which a log-linear matching function is included	
Berman 1997	notified	time trend	log-linear
Gross 1997	notified	real wages real energy price	log-linear (with co-integration analysis)
Gregg and Petrongolo 1997	notified	time dummies	non-linear
Bell 1997	notified notified notified, adjusted	time trend, benefits, mismatch demographic variables, LTU/U	log-linear (with co-integration analysis)
Bleakley and Fuhler 1997	help-wanted index adjusted	structural breaks	log-linear
Coles and Smith 1998	V stock V inflow	time trend	log-linear
Mumford and Smith 1999	—	new hires, other groups of job seekers, LTU/U	log-linear
Yashiv 2000	notified	structural breaks	log-linear; translog

TABLE 2
SECTORAL MATCHING FUNCTION STUDIES

Author	Country and coverage	Period and frequency	Level of disaggregation	Dependent variable
Burda 1993	Czech Rep. Slovakia	1990–92 monthly	76 districts 38 districts	hires from U
Bennet and Pinto 1994	Britain, men	1967–83 quarterly	104 local districts	unempl. outflow
van Ours 1995	Netherlands	1981–83 annual	8 regions	hires from U ; hires from N
Coles and Smith 1996	England and Wales	1987	257 TTWAs	filled vacancies
Boeri and Burda 1996; Profit 1997	Czech Republic	1992–94 quarterly	76 districts	hires from U
Burda and Profit 1996	Czech Republic	1990–94 monthly	76 districts	hires from U
Burgess and Profit 1998	U.K.	1985–95 monthly	303 TTWAs	unempl. outflow; filled vacancies
Profit and Sperlich 1998	Czech Republic	1992–96 monthly	76 districts	hires from U
Broersma and van Ours 1999	Netherlands	1988–94 quarterly	6 industries	hires from U ; filled vacancies
Münich, Svejnar, and Terrel 1999	Czech Rep. Slovakia	1991–96 monthly	76 districts 38 districts	hires from U ; hires from N
Anderson and Burgess 2000	U.S.	1979–84 quarterly	4 states \times 20 industries	all new hires; hires from non-empl.; hires from empl.

elasticity estimates when flows from unemployment to non-employment are ignored, which we discuss when we look at the estimates in more detail.

The aggregate estimates also find that there are other variables that influence matching in a systematic way. Disaggregate estimates, summarized in table 2, have not contradicted the aggregate estimates but concentrated instead on finding out what are those other variables, and whether aggregation intro-

duces biases that can be estimated. Hazard studies also focus on identifying other influences on transitions, especially those related to individual characteristics. With the number of estimates growing significantly in recent years, it is natural that there are estimates of both increasing and decreasing returns to scale. But such divergencies from constant returns are only mild and rare. The stylized fact that emerges from the empirical literature is that there is a

TABLE 2 (Cont.)

Author	Job seekers	Job vacancies	Other variables	Specification
Burda 1993	unemployed	notified		log-linear
Bennet and Pinto 1994	unempl. rate	vacancy rate		log-linear
van Ours 1995	unempl. + empl. seekers	all vacancies	reg. dummies	non-linear
Coles and Smith 1996	unemployed	notified	wages, size of TTWA, demographic variables	log-linear
Boeri and Burda 1996; Profit 1997	unemployed	notified	time dummies, area dummies, lagged dep. var.	log-linear
Burda and Profit 1996	unemployed	notified	time dummies, spillover effects across areas	log-linear
Burgess and Profit 1998	unemployed	notified	time trends, spillover effects across areas	log-linear
Profit and Sperlich 1998	STU and LTU	notified	area dummies, lagged dep. var.	log-linear; nonparametric
Broersma and van Ours 1999	unemployed; $U + \text{non-}U$ seekers	notified	industry dummies	log-linear
Münich, Svejnar, and Terrel 1999	STU and LTU	notified	human capital, output per head, demographic variables	translog
Anderson and Burgess 2000	unempl. rate	help-wanted rate	Δ employm. in ind., replacement ratio, demographic variables	log-linear

stable aggregate matching function of a few variables that satisfies the Cobb-Douglas restrictions with constant returns to scale in vacancies and unemployment.

Table 3 summarizes the results of studies that tested for constant returns. The estimates of Burda and Wyplosz (1994) for some European countries show decreasing returns to scale. Those of Blanchard and Diamond (1990b) and the translog specifications of Ronald Warren (1996) for U.S. manufacturing;

Eran Yashiv (2000) for Israel; and Daniel Münich, Jan Svejnar, and Katherine Terrell (1999) for the Czech Republic (and in some cases Slovakia) show increasing returns. All other estimates support constant returns.

3. *Microfoundations*

What are the reasons for the existence of a well-behaved matching function and what are the other variables

TABLE 3
EVIDENCE ON THE RETURNS TO SCALE IN THE MATCHING FUNCTION

Author		coef[ln U] (<i>t</i> – stat.)	coef[ln V] (<i>t</i> – stat.)	CRS test (if any)	<i>R</i> ²
<i>Log-linear specifications</i>					
Pissarides 1986	U.K.	0.70 (unrestricted estimates not reported)	0.30	<i>p</i> = 0.74	
Blanchard and Diamond 1990b	OLS	0.35 (3.9)	0.54 (6.9)		0.47
	IV (1)	0.60 (2.4)	0.75 (4.0)		0.43
	IV (2)	0.42 (2.3)	0.62 (4.3)		0.41
	OLS (Manuf.)	0.67 (7.2)	0.71 (14.7)		0.92
Layard et al. 1991	U.K.	0.81 (6.6)	0.19 (6.6)	(unrestricted estimates not reported)	<i>p</i> = 0.24
van Ours 1991	Netherlands	0.48 (2.8)	0.67 (7.4)		0.93
Burda 1993	Czech Rep.	0.42 (3.5)	0.44 (3.3)	<i>p</i> > 0.05	
	Slovakia	0.61 (3.0)	0.10 (0.9)	<i>p</i> > 0.05	
Burda and Wyplosz 1994	France	0.52 (13.7)	0.09 (2.59)	<i>p</i> = 0.00	0.95
	Germany	0.68 (25.1)	0.27 (11.3)	<i>p</i> = 0.06	0.97
	Spain	0.12 (1.67)	0.14 (3.0)	<i>p</i> = 0.00	0.97
	U.K.	0.67 (21.1)	0.22 (6.78)	<i>p</i> = 0.02	0.93
Bennet and Pinto 1994	Britain	sum of elasticities: 0.65 – 1.15 (90% of 104 regressions)			
Coles and Smith 1996	England and Wales	0.34 (10.6)	0.66 (16.0)		0.91
Berman 1997	Israel	0.29 (3.22)	0.39 (4.33)	<i>p</i> = 0.07	0.67
Anderson and Burgess 2000	All new hires	0.43 (2.4)	0.81 (4.0)	<i>p</i> = 0.49	0.86
	New hires from NE	0.39 (2.2)	0.75 (3.8)	<i>p</i> = 0.67	0.86
	New hires from E	0.54 (1.1)	0.87 (1.6)	<i>p</i> = 0.67	0.61
Yashiv 2000		0.49 (6.1)	0.87 (14.5)	<i>p</i> = 0.00	0.97

TABLE 3 (Cont.)

Author		coef[ln U] (<i>t</i> - stat.)	coef[ln V] (<i>t</i> - stat.)	CRS test (if any)	R ²
<i>Translog specifications</i>					
Warren 1996		sum of elasticities: 1.33 (sample mean)		<i>p</i> = 0.03	0.56
Münich et al. 1999	Czech Rep.	1.54 – 2.51 (sample mean)	0.65 – 1.00 (sample mean)		
	Slovakia	0.34 – 2.62 (sample mean)	0.17 – 0.25		
Yashiv 2000		0.28 (sample mean)	0.80 (sample mean)	<i>p</i> = 0.00	0.97

Notes: *p* denotes the *p*-value for the rejection of constant returns to scale.

that influence the matching rate? In order to answer these questions we need to look at the microfoundations behind the aggregate matching function. The literature has done that; but although there are several microeconomic models that can be used to justify the existence of an aggregate matching function, none commands universal support and none convincingly says why the aggregate matching function should be of the Cobb-Douglas form. The literature has had more success, however, in suggesting what should be the other variables that influence the matching rate.

The other variables can be classified into two groups. The first group includes everything that individuals do during search, such as choosing how many applications to make, changing their advertising methods, etc. The second includes shifts unrelated to individual search decisions. We take up the second group first. Most of the theoretical work on matching functions studies individual behavior and is discussed in the subsections that follow.

3.1 Mismatch

The shifts in the matching function that are unrelated to search decisions

are due to technological advances in matching and to aggregation issues. Technological advances include reforms such as the computerization of employment offices, job advertising on the internet, an increase in the resources that governments put into subsidized matching, and other similar changes. Although changes of this type have been observed recently in most industrial countries (see OECD 1994, ch. 6; 1999) and they have influenced the matching process to the extent that the OECD recommends them to its members as the most cost-effective “active” labor market policies, they have attracted little formal theoretical or empirical work.

Aggregation issues have attracted more attention from labor economists, often disguised under the label “mismatch.” Mismatch is an empirical concept that measures the degree of heterogeneity in the labor market across a number of dimensions, usually restricted to skills, industrial sector, and location. Large differences in the skills possessed by workers and those required by firms would lengthen the time that it takes to match a given group of workers to a given group of

firms, as agents search for a good match among the heterogeneous group. Industrial sector matters in matching because of industry-specific skills that may not be picked up by generally available measures of skills. Finally, location influences matching because of imperfect labor mobility. Although the term “mismatch” has been used in the literature to describe all three dimensions (see Richard Layard, Stephen Nickell, and Richard Jackman 1991), the term “imbalance” in numbers in the local market has been used before to describe differences in the distribution of locations (see, e.g., Charles Holt 1970b) and is a useful way of distinguishing between skill mismatch and differences in location.

If mismatch and imbalance in an economy were identically zero in all their dimensions, the matching function would not exist and jobs and workers would match instantaneously. It is because of the existence of some mismatch that meetings take place only after a search and application process. If there is an exogenous rise in mismatch, the rate of job matches at given inputs must fall, implying a shift in the aggregate matching function.

Of course, if empirically mismatch changes frequently in ways that cannot be accurately measured, the usefulness of the concept of the matching function is reduced. But this requirement is not different from the one on other aggregate functions in the macroeconomist's tool kit. Some of the early controversies in production theory (like the capital controversy of the two Cambridges) were about the question whether factors of production could be aggregated into two or three composites that enter a single-valued differentiable production function. Whether in practice aggregation problems are serious enough to question the usefulness of the match-

ing function is an empirical question. The available evidence does not support serious aggregation problems that cannot be dealt with empirically.

In the empirical literature, mismatch, or imbalance, bears some relationship to the frequently discussed “sectoral shifts hypothesis,” and to the older view of “structural” unemployment, which was thought to be unemployment arising from fast structural change in the economy as a whole. For example, it has been argued that the oil, technology, and other supply shocks of the 1970s and 1980s increased the speed with which unemployed workers needed to adapt to the changing requirements of employers. This led to increased mismatch between the skills possessed by workers and the skill requirements of employers, which increased the duration of unemployment (and hence the stock of unemployment) at given vacancies.

David Lilien (1982) argues that imbalance in the distribution of jobs and workers changes over the business cycle, to the extent that it can adequately explain the observed fluctuations in aggregate employment. Although he finds that his sectoral shifts hypothesis has some success in explaining U.S. employment data, his findings have been effectively criticized by Katharine Abraham and Lawrence Katz (1986) and Blanchard and Diamond (1989). Their critiques point to the fact that the observed positive correlation between the dispersion of employment growth and the unemployment rate can be produced either by sectoral shifts or by aggregate demand fluctuations. Information on job vacancies allows one to distinguish between the two explanations. The strong negative correlation between unemployment and vacancies supports an aggregate-demand interpretation of U.S. employment fluctuations rather than one based on sectoral shifts.

Similar conclusions can be reached from the observation that job creation and job destruction rates across sectors are negatively correlated over the cycle (see Davis, Haltiwanger, and Schuh 1996).

Layard, Nickell, and Jackman (1991, ch. 6) follow a different approach and measure mismatch by the variance of sectoral unemployment rates. They show, however, that their measure of mismatch cannot account for the shifts in the aggregate matching function or the variance in U.K. unemployment. More recently, Marco Manacorda and Petrongolo (1999) propose a measure of skill mismatch that makes use of information about the demand and the supply of skills, represented respectively by productivity parameters and labor force shares. This leads them to the conclusion that the unbalanced evolution of the demand and the supply of skills can explain some of the rise in unemployment in Britain, and hence some of the observed shifts in the matching function, but still not all.

On balance, neither the sectoral shifts hypothesis nor mismatch has had much success in accounting for a large fraction of fluctuations in employment or for the secular rise in unemployment in some countries. So although empirical mismatch variables can account for some of the shifts in the aggregate matching function, we should look elsewhere for the main shift variables. But some authors (for example Horst Entorf 1998) argue that the measurement of mismatch in aggregate studies of matching functions still suffers from many problems, and may be able to account for more of the unexplained variance in matchings than is currently found in the literature.

If aggregation problems are not an issue, what can account for the matching function and what else can shift it?

3.2 *Coordination Failures*

The first matching function owes its origins to a well-known problem analyzed by probability theorists, that of randomly placing balls in urns (Gerard Butters 1977; Robert Hall 1979; Pissarides 1979; Kevin Lang 1991; James Montgomery 1991; and Blanchard and Diamond 1994). Firms play the role of urns and workers the role of balls. An urn becomes “productive” when it has a ball in it. Even with exactly the same number of urns and balls, a random placing of the balls in the urns will not match all the pairs exactly, because of a coordination failure by those placing the balls in the urns. Some urns will end up with more than one ball and some with none. In the context of the labor market, if only one worker could occupy each job, an uncoordinated application process by workers will lead to overcrowding in some jobs and to no applications in others. The imperfection that leads to unemployment here is the lack of information about other workers’ actions, though simple extensions could enrich the source of frictions.

In the simplest version of this process U workers know exactly the location of V job vacancies and send one application each. If a vacancy receives one or more applications it selects an applicant at random and forms a match. The other applicants are returned to the pool of unemployed workers to apply again. The matching function is derived by writing down an expression for the number of vacancies that do not receive any applications. Given that each vacancy receives a worker’s application with probability $1/V$, and there are U applicants, there is a probability $(1 - 1/V)^U$ that a given vacancy will not receive any applications at all. Therefore, the number of matches that take place at each application round is

$$M = V[1 - (1 - 1/V)^U]. \quad (2)$$

For a large V a good approximation to $(1 - 1/V)^U$ is the exponential $e^{-U/V}$, giving the matching function

$$M = V(1 - e^{-U/V}). \quad (3)$$

This matching function clearly satisfies the properties satisfied by the general function in (1), and in addition it satisfies constant returns to scale. It is, however, too naive to be empirically a good approximation to matching in real labor markets. For example, it implies an implausible combination of levels and durations of unemployment. If the level of unemployment and vacancies is the same, the mean duration of unemployment is 1.58 periods, and if the level of unemployment is three times as high as that of vacancies, mean duration is 3.16. In actual labor markets duration would rise by more than the function (3) implies when the level of unemployment is higher.

The introduction of small additional frictions to the urn-ball framework can enrich the matching function considerably. We consider three related extensions. In the first, workers do not know the firms with the vacancies and choose at random one firm to apply. Then the probability that a vacancy receives no applications is $(1 - 1/(N + V))^U$, where N is the level of employment. If in addition the labor force size is L , $N = L - U$, the matching function becomes

$$M = V(1 - e^{-U/(L - U + V)}). \quad (4)$$

This matching function exhibits increasing returns to scale in U and V and may even fail the assumption of diminishing returns to unemployment, though this would require more vacancies than employment. But it satisfies constant returns to L , U , and V , so it avoids the counterfactual implication that larger countries should have lower equilibrium unemployment rates than otherwise identical smaller countries.

In the second extension, not all workers are suitable for the vacancies available but the worker does not know which vacancies are suitable. Let K be the fraction of workers who are suitable employees for a randomly selected vacancy. The probability that a vacancy will not be visited by a worker is still $1/V$ but only KU workers can now take the job. The matching function therefore generalizes to

$$M = V(1 - e^{-KU/V}), \quad (5)$$

with the inverse of K standing as an index of mismatch between the available jobs and workers.

Our third extension gives a similar matching function but the new parameter is associated with search intensity. Each period a fraction $1 - s$ of the unemployed do not apply for a job. This fraction rotates, so each unemployed worker misses one application round out of every $1/(1 - s)$ rounds. Then, the probability that a given vacancy receives no applications during a given application round is $(1 - 1/V)^{sU}$, giving the matching function

$$M = V(1 - e^{-sU/V}). \quad (6)$$

Both (5) and (6) satisfy all the properties of (1) for given K and s , but in addition open up the possibility of modeling mismatch and the frequency of applications, and so bringing the simple form (3) closer to the data. The mean duration of unemployment for these functions is again U/M and so more imbalance or a lower application frequency gives the longer mean durations for given vacancy-to-unemployment ratio that the data suggest. We take up the question of what might determine s next.

3.3 Worker Heterogeneity: Search Intensity and Reservation Wages

The hazard rates (or unemployment durations) derived in the preceding

section were for “representative” individuals, without explicit dependence on individual characteristics. Yet, in empirical estimates, it is found that individual characteristics play an important role in accounting for differences in hazard rates across individuals. In this subsection and the next, we suggest two ways of introducing the influence of individual characteristics in the matching technology and show what this does to the aggregate matching function.

Worker heterogeneity is most conveniently introduced into the matching function by making the assumption that the intensity of search is a choice variable. We define intensity of search as the number of “units” of search supplied by a given individual. Units are defined as follows. If individual i supplies s_i units of search and individual j supplies s_j units, then in a small time interval individual i is s_i/s_j times more likely than individual j is to find a match. Search units are supplied at a cost, which is normally increasing, and they are chosen optimally to maximize the net returns from search (Pissarides 2000, ch. 5). Therefore, different individuals will choose a different number of search units, depending on their search costs, the cost of unemployment, and the expected returns from employment.

To derive the matching function implied by this extension, let s be the average number of search units supplied by an unemployed person.⁵ Then, the total number of search units supplied is sU , and so the aggregate matching function is

$$M = m(sU, V), \tag{7}$$

a more general form of (6). Of course, varying intensity could also be introduced for job vacancies, in symmetric

fashion. The hazard rate for an individual who supplies s_i units of search is $s_i m(sU, V)/sU$. The fact that this function depends on individual characteristics through the optimal choice of intensity of search justifies the econometric estimates of hazard functions that make use of individual survey data. On average, the representative individual will choose intensity s , so the average transition rate for unemployed workers, which can be used in macro modeling, is $m(sU, V)/U$.

Another channel through which heterogeneity can influence the matching function and market outcomes arises when there is a distribution of wage offers. The distribution may be due either to identical firms offering different wages, as in the model of Kenneth Burdett and Mortensen (1998), or to match heterogeneity, as in the model of Boyan Jovanovic (1979). The individual chooses a reservation wage and rejects all wage offers below the reservation. In equilibrium models the reservation wage for each job that the worker encounters is such that neither the firm nor the worker will want to form a match if the wage is below reservation (Pissarides 2000, ch. 6). Of course, if individual characteristics differ, workers may choose different reservation wages.

Let $m(U, V)$ be the technology that brings vacant jobs and unemployed workers together. When a pair meets, it is faced with a wage offer w , which is assumed to be a drawing from a probability distribution $G(w)$. If the probability distribution is known to job seekers, the optimal policy of individual i is characterized by a reservation wage R_i , such that the job is accepted if $w \geq R_i$, and rejected otherwise. The hazard rate for this individual is $[1 - G(R_i)]m(U, V)/U$. Aggregation over all individuals gives the average transition rate, and from there, multiplication by the unemployment rate gives the aggregate

⁵ This s bears a close resemblance to the s of the preceding section, which explains the use of a common symbol.

matching function. Clearly, given that in general the probability $G(R_i)$ is nonlinear, the aggregate function takes a rather complicated form, but to a first approximation we can define R as the average reservation wage and write the aggregate matching function as

$$M = [1 - G(R)]m(U, V). \quad (8)$$

As with the function derived for variable search intensity, (7), this function justifies the introduction of aggregate variables that influence individual decisions during search into estimated matching functions. The variables can be demographic variables that influence the intensity of search—for example, if youths search with lower intensity than adults, the youth share in the population should be a shift variable. Or they can be variables that influence the cost of search and moving, such as unemployment insurance and housing transactions. The list of variables that can influence search intensity and reservation wages has been a fertile ground for searching for statistically significant shift variables in empirical matching functions, an issue discussed in the empirical sections that follow.

3.4 *Ranking*

Blanchard and Diamond (1994) consider the alternative assumption that firms receive many applications at a time and have preferences over job applicants. They rank applicants and offer the job to the person first in the rank. Their motivation for studying this process is a feature of European labor markets, that with the rise in unemployment durations, the long-term unemployed became “disenfranchised” and less desirable employees than those with more recent work experience.

The matching function used by Blanchard and Diamond (1994) is simi-

lar to the urn-ball function (3), but the implications of the ranking principle can be illustrated more generally. Suppose the unemployed are divided into two groups, the short-term unemployed and the long-term unemployed. Let the number of short-term unemployed be U^S and the number of long-term unemployed be U^L . Then, if a short-term and a long-term unemployed compete for the same job, the short-term unemployed always gets it. Therefore, the long-term unemployed do not cause congestion for the short-term unemployed during search, and the long-term unemployed get only jobs for which there are no short-term applicants. The implication of the first claim is that the matching function for the short-term unemployed is $m^S(U^S, V)$, where V are all the vacancies, and the matching function satisfies all the properties of (1). If the long-term unemployed knew which vacancies are now being taken by the short-term unemployed, their matching function would be $m^L(U^L, V - M^S)$. But more generally, if there is a coordination failure between short-term and long-term unemployed, we write as usual $m(U^S + U^L, V)$ for total matches and then attribute the difference between M and M^S to matches involving long-term unemployed. That is, the aggregate matching function is

$$M = m(U^S + U^L, V) \quad (9)$$

but the hazard rate for the short-term unemployed is $m^S(U^S, V)/U^S$ and for the long-term unemployed $m(U^S + U^L, V)/U^L - m^S(U^S, V)/U^L$.⁶ Simple calculations show that if the matching functions are identical, the hazard rate of the short-term

⁶ Note that the expected duration of unemployment of the long-term unemployed is the inverse of their hazard rate, but for the short-term unemployed account has to be taken of the fact that if they survive to long-term unemployment, their hazard rate will fall.

unemployed is always higher than the hazard rate of the long-term unemployed.

Blanchard and Diamond (1989) estimate a specification similar to (9) and impose that the short- and long-term unemployed are perfect substitutes up to a scale parameter. If the estimated value of this parameter is below one it is evidence in favor of the ranking hypothesis. Their point estimate of the scale parameter, however, slightly exceeds one, but is not significantly different from zero.

3.5 *Stock–Flow Matching*

The matching functions discussed so far were derived under the assumption that job seekers take a vacant job at random and apply for it. This assumption is convenient and realistic in many situations, given that there is an element of luck in hearing about job offers. But there is also a systematic element in search. This subsection and the next discuss the derivation of an aggregate matching function from assumptions that go to the other extreme of no randomness in job applications.

Melvyn Coles (1994) and Coles and Eric Smith (1998) consider the implications of the assumption that job seekers have complete information about the available job vacancies and apply simultaneously to all the ones that they think are likely to be acceptable. Let this number be the entire universe of jobs on offer. But because of heterogeneity, not all job matches turn out to be acceptable. Let a constant α be the probability that a job match is unacceptable to the pair. A matching round then begins in a “marketplace.” Job–worker pairs that made contact and are unacceptable are rejected. The remaining acceptable ones are sorted out so that no firm and worker who could form an acceptable match remain unmatched. Thus, unlike the urn-ball process of the

preceding example, there is no coordination failure in this case. Those workers who remain unmatched do so because there are no vacancies suitable for them among the existing pool.

It follows that no job vacancy or unemployed worker who has been through one round of matching will attempt to match again with a pre-existing job seeker or vacancy. Of course, the assumption that the length of time when job seekers and vacant jobs get to know each other is one matching period is a simplifying one. Coles and Smith’s assumption captures a realistic feature of search markets, that a job seeker scans a lot of advertisements before deciding where to apply, and once an advertisement has been scanned and rejected, return to it is less likely than application to a new advertisement.

Under Coles and Smith’s assumption there is a sharp distinction between the stocks of unemployed workers and vacant jobs and the new inflows. The stock of unemployed workers at the beginning of the period will not match with the stock of vacant jobs also at the beginning of the period, because they were both participants in the matching round in the previous period. The resulting matching process is therefore one where the unmatched stock of traders on one side of the market is trying to match with the flow of traders on the other side. This is often referred to as “stock–flow” matching.⁷

Let the stocks at the beginning of the period be U and V . If the flow of new unemployed workers and new job vacancies into the respective pools during the period are u and v , the U initial workers match with the new inflow v only, whereas the inflow u matches with both V and v . Coles and Smith consider

⁷ Coles (1999) discusses the turnover externalities implied by stock–flow matching.

a period of infinitesimal length and so ignore the probability of a newly unemployed worker matching with a newly created vacant job. In this case, the probability that a new vacancy is matched on entry is $1 - \alpha^U$, so the matches due to new vacancy creation are $v(1 - \alpha^U)$. Recall that α is the probability that a random pairing is unacceptable. The probability that a new worker is matched on entry is $1 - \alpha^V$ and so the new matches due to the new entry of workers is $u(1 - \alpha^V)$. Since there are no matches between old unemployed and old vacancies, the sum of the two matches gives the entire matching rate in the economy. That is, the matching function is

$$M = v(1 - \alpha^U) + u(1 - \alpha^V), \quad (10)$$

with $1 > \alpha > 0$.

The hazard rate for workers who are unemployed at the beginning of the period is $v(1 - \alpha^U)/U$ and for the new inflow $1 - \alpha^V$. The latter is likely to be bigger because for the short period under analysis, the stock of jobs and workers is likely to be much bigger than the new flow, i.e., v is likely to be much smaller than U . In the data usually hazard rates for recently unemployed workers are much bigger than those who have been unemployed longer, although many other reasons can contribute to this difference.

The matching function in (10) exhibits increasing returns to scale in the stocks and the flows, although it is not homogeneous. The reason is that job seekers apply to all the available job vacancies simultaneously. If we double the number of job vacancies and unemployed workers, the applications of each and every job seeker double. This contrasts with the matching function in (3), where each job seeker applies only to one job and so doubling the number of jobs doubles the number of applica-

tions. Applying to more than one vacancy at a time is a realistic feature of the application process but it depends on a constant rejection probability α . When the rejection probability is endogenized, we would expect it to increase when the matching probability increases. Intuitively, the model captures the fact that in a large market job seekers have more options but not the fact that they would be more choosy as a result.

The model implies that the matching probability for the unemployment inflow does not suffer from congestion, whereas the pre-existing unemployed suffer congestion from each other. This result derives from the assumption that newcomers flow into the market individually, given the continuous time structure of the matching process that takes place across time periods of infinitesimal length. If instead we consider time periods of discrete length, a newly unemployed can match with a new vacancy, and at the same time all the newly unemployed can cause congestion to one another when trying to match with existing vacancies. The extra congestion externalities generated in this case are shown by Paul Gregg and Petrongolo (1997) to rule out increasing returns to scale.

Stock-flow matching has received some empirical support. Coles and Smith (1998) argue that, due to stock-flow matching, exit rates are higher when traders first enter the labor market, and drop sharply thereafter. This suggests that traders who are unlucky at their first round of search need to wait and queue for new entrants in order to find a suitable match. There are, however, many other reasons for the fall in unemployment exit rates, which include ranking, discouragement, and loss of skills during unemployment. But more detailed evidence on matching combinations

among labor market participants shows that stock–flow matching plays a significant role in raising the matching probabilities of recently unemployed workers.

Coles and Smith estimate a log-linear matching function dividing the outflow from unemployment into duration classes. They find that both the stock and the inflow of vacancies increase the unemployment outflow at short durations of search but at longer durations only the inflow of new vacancies increases significantly the job-finding rates of the unemployed. Qualitatively similar results are also found by Gregg and Petrongolo (1997), who estimate quasi-structural outflow equations for unemployment and vacancies derived from a stock–flow matching model in discrete time.

3.6 Aggregation over Distinct Markets

We finally discuss a derivation of the aggregate matching function that relies on the existence of disequilibrium in micro markets and limited mobility of labor. The assumption is that the economy is divided into micro markets that do not suffer from frictions but suffer from a disequilibrium in the sense that the demand for labor in each market is not equal to the supply. There is no mobility of labor or capital between markets. This assumption can be interpreted as the source of the friction that gives rise to the aggregate matching function. It implies that markets with unemployment can coexist with markets with job vacancies, although no market has both. Aggregation over all markets gives an aggregate function that contains both vacancies and unemployment. With perfect mobility workers would move until the short side of the aggregate economy cleared and no aggregate matching function would exist.

A model of this form was first used by

Bent Hansen (1970) to derive the Beveridge curve and by Holt (1970b) to derive an expression for structural unemployment. Other studies that follow this approach are Jacques Drèze and Charles Bean (1990), Samuel Bentolila and Juan Dolado (1991), and Wolfgang Franz (1991). Borrowing results discussed by Drèze and Bean (1990, p. 14), who credit Jean Paul Lambert (1988) for the derivations, let the ratio of inputs of firms and workers into search (say the number of vacancies and unemployment that initially enter the market) in each micro market be log-normally distributed. Then, if the short side of each market clears, namely, if the matching function in each market is $M_i = \min(U_i, V_i)$, and U and V are the aggregate quantities, there is a CES-type relationship that could be interpreted as an aggregate matching function

$$M = (U^{-\rho} + V^{-\rho})^{-1/\rho}, \tag{11}$$

where $\rho > 0$ is related to the variance of the ratio of unemployment to vacancies across micro markets.

The derivation of this matching function needs the assumptions of exogenous distributions of unemployment and vacancies across space. Ricardo Lagos (2000) derives instead optimal rules for the allocation of agents across space, under the assumption that there is uncertainty about the number of agents at each location. He shows that the resulting matching equilibrium is one where the short side of the market clears—but now the number of agents on one side is optimally selected (see also Lagos and Gianluca Violante 1998).

As far as we are aware, there are no tests of this microfoundation for the aggregate matching function. A key problem here is to define the unit of the micro market. If a micro market is infinitesimally small, and consists of at most one job, the assumption is trivially

correct. If it is large and equal to the economy as a whole, the assumption is incorrect, since at the aggregate level vacancies and unemployment coexist. A travel-to-work area would appear to be the most appropriate disaggregation level, but no tests have been conducted at this level. Another difficulty with the CES form is that it relies on distributional assumptions about unemployment and vacancies, and a test of the CES restrictions (e.g., versus Cobb-Douglas) would need to test the validity of the distributional assumptions as well.⁸

4. Empirical Methods and Findings

In the matching framework the equilibrium levels of unemployment and job vacancies that persist in steady state are the result of the intensity of the job reallocation process and of the matching effectiveness of the labor market. One way of making inferences about the empirical properties of the matching function is to estimate such a long-run vacancy-unemployment relationship, the *UV* or Beveridge curve. The advantage from taking this indirect route is that estimation of the Beveridge curve requires only data on stock variables, not flows, which are more readily available. The early literature on matching followed mainly this approach. But partly because of the difficulty of making accurate inferences about the matching function from estimated Beveridge curves (outlined below) and partly because the connection between the matching function and the Beveridge curve became better understood, most of the empirical literature since the late 1980s and early 1990s estimated di-

rectly the matching function. As more data became available, estimated matching functions appeared in the literature making use of aggregate time-series for the whole economy or for some sector (most frequently manufacturing), panel data for regions or districts, and data on individual re-employment hazards. We review the main results of each approach with focus on the results not previously discussed.

4.1 Beveridge Curves

A steady-state relationship between the unemployment rate and the vacancy rate can be derived from the simple matching function (1). Let U and V be the number of unemployed workers and job vacancies respectively, and N and L the level of employment and the labor force (so $L = N + U$). Define the unemployment rate $u = U/L$ and let the vacancy rate be $v = V/N$ (an inconsequential change from the alternative $v = V/L$). Assume also that the job separation rate is λ , so total separations are $S = \lambda N$. Then, imposing constant returns to scale on $m(\cdot)$ and noting that in steady state the number of matches M equals the number of job separations S , we get the Beveridge curve,⁹

$$\lambda = m\left(\frac{U}{L}, \frac{V}{N}\right) = m\left(\frac{u}{1-u}, v\right). \quad (12)$$

Given the separation rate λ , our assumptions on $m(\cdot)$ imply a negative steady-state relationship between the unemployment rate and the vacancy rate.

An aggregate Beveridge curve of the form of equation (12) was estimated by a number of authors for the aggregate stocks of vacancies and unemployment

⁸ Graph theory can also potentially be used to derive results about the interaction of agents in markets with frictions, although there are as yet no clear-cut implications for the aggregate matching function. See Yannis Ioannides (1997).

⁹ Note that constant returns in U and V are not needed here. Suppose for example that the matching function has constant returns in U , V , and N , as in (4) but increasing returns in U and V . Then dividing through by N gives an expression with properties similar to (12).

(see Jackman and Stephen Roper 1987; Alan Budd, Paul Levine, and Peter Smith 1988; Jackman, Layard, and Pissarides 1989, and Howard Wall and Gylfi Zoega 1997 for Britain; Abraham 1987 for the United States; Franz 1991 for Germany; Per-Anders Edin and Bertil Holmlund 1991 for Sweden; Giorgio Brunello 1991 for Japan; and Jackman, Pissarides, and Savvas Savouri 1990 for a multicountry study). The form preferred is usually log-linear, which implies a Cobb-Douglas matching function if the foundation for the Beveridge curve is the aggregate matching function. All studies establish the existence of a negative long-run relationship between the vacancy rate and the unemployment rate, as implied by (12). But virtually all studies also identify some shift variables not present yet in (12).

Of course, (12) is consistent with many different micro frameworks, some perhaps unrelated to the matching framework. But if we posit that there is an aggregate matching function underlying (12), some lessons immediately emerge from the Beveridge curve studies about the properties of this matching function.

First, there is support for the restrictions on the simple two-variable matching function, including some tentative evidence for constant returns. The negative convex-to-the-origin shape predicted by the model fits the data well and in the cross-country regressions country size does not appear to be an influence on the position of the Beveridge curve, something that would be implied by some models of increasing or decreasing returns to scale. But no study conducts a careful test of increasing returns to scale by testing, for example, whether the matching rate improves when the total number of participants increases for a given ratio of vacancies to unemployment, or whether

there are increasing returns to U and V but constant returns to U , V , and L , as implied for example by (4).

Second, there have been shifts in the relationship, especially in European countries. These shifts coincide with the secular rise in European unemployment, which started in the mid-1970s. The unemployment rate has increased despite the fact that the separation rate and the vacancy rate, λ and v in (12), have not shown any trend. The implication for the matching function is that there are variables besides u and v that have played an important role in matching in the last two decades and these variables contributed to a deterioration of the matching rate.

Reasons that have been suggested in the literature include mismatch (Jackman, Layard, and Pissarides 1989)—which, as we have seen, may explain some but not much of the shift—the growth in long-term unemployment, which reduces both the search intensity of the unemployed and their employability through loss of skill (Budd et al. 1988), the generosity of the unemployment insurance system (Jackman et al. 1989) and active labor market policy (Jackman, Pissarides, and Savouri 1990). Jackman and Roper (1987) have shown that in Britain the shifts in the regional Beveridge curves were of the same order of magnitude as the aggregate curve, casting doubt on the power of regional mismatch to explain the shift in the aggregate curve. On a more positive note, Jackman et al. (1990) show that the different position of the estimated Beveridge curves in Europe is positively correlated with their spending on active labor market policies. Countries with more spending on policies that aid matching have Beveridge curves closer to the origin.

But on average, no single or combination of variable(s) can account for the

deterioration of the matching rate since the mid-1970s, and the literature often attributes it to unmeasured elements of the unemployment insurance system and mismatch. It is interesting that measured components of the unemployment insurance system do not play a role in the deterioration of the matching rate. Unmeasured elements mentioned in the literature are usually statements about the leniency of the system and its coverage. In the estimation, such measures are usually picked up by time trends, which could of course account for many other unobserved or unidentified influences on matching.

Estimation of log-linear UV curves, along the lines followed by most of the studies mentioned, suffers from some problems connected with the assumption of flow equilibrium, the endogeneity of the separation rate, and the fact that inferences about the micro process underlying matching cannot be easily made from such an aggregate framework. More recent studies estimate matching functions by making use of flow data, which are more disaggregated and do not have to rely on either a constant (or exogenous) job separation rate or flow equilibrium.

4.2 Aggregate Studies

Table 1 gives a summary of the specifications and the results of studies that have estimated aggregate matching functions. Pissarides (1986) estimates an aggregate matching function for Britain over the period 1967–83. The specification uses quarterly data, with the average monthly outflow rate from male unemployment during the quarter as the dependent variable. The unemployment series used is for registered male unemployment and the series for vacancies is notified vacancies adjusted upwards for

incomplete coverage.¹⁰ Results with both linear and log-linear specifications are reported. The estimated log-linear specification is

$$\ln\left(\frac{M}{U}\right)_t = \alpha_0 + \alpha_1 \ln\left(\frac{V}{U}\right)_t + \alpha_2 t + \alpha_3 t^2 \quad (13)$$

+ lags + structural variables.

Both the linear and log-linear specification strongly support constant returns to scale in U and V (see table 3). The estimated elasticity of matching with respect to vacancies is 0.3 with an implied elasticity with respect to unemployment 0.7. No other variables were found to be significant except for the time trends, which indicate a large fall in the rate of job matching at given unemployment and vacancy rates during the sample period.

Later estimation of a similar regression by Layard, Nickell, and Jackman (1991, ch. 5) for 1968–88 found similar elasticity estimates but also found that the rise in long-term unemployment reduces the matching rate at a given unemployment rate. But the time trend remains significant in their regression. Also, the authors do not deal with the endogeneity of long-term unemployment but measure its impact by computing an index for duration effects. This index is a weighted average of

¹⁰ Reported vacancy data are generally unreliable. In several countries (including the United Kingdom, France, Germany, and Israel), data on job vacancies are collected on a regular basis. The data, however, are for vacancies notified to state employment agencies and they suffer from underreporting, with the exception of some rare instances where reporting is mandatory (see, e.g., Eran Yashiv 2000). In addition, the proportion of vacancies notified varies with general economic conditions, both aggregate and sectoral (see Jackman et al. 1989). Jackman et al. suggest an adjustment method to correct for the underreporting, which makes use of information contained in the fraction of job matches realized through state employment agencies. In the United States there is no comparable vacancy series. The proxy most frequently used is the help-wanted index, which is based on the counts of job advertisements in major metropolitan newspapers (see Abraham 1987).

duration with fixed weights that are proportional to the outflow rates from each category in a base year. The fact that outflow rates fall with duration and duration increases during the sample gives an upward trend to the index, which is positively correlated with the trend in unemployment.

Long-term unemployment has been a frequent candidate for shifts in the aggregate matching function (see Budd, Levine, and Smith 1988). Although this is related to Blanchard and Diamond's (1994) idea of ranking, it is more general, in the sense that the claim being made is that the average matching rate should be higher the lower the incidence of long-term unemployment.¹¹ Denoting again the stock of short-term unemployed by U^S and the stock of long-term unemployed by U^L , this implies that the aggregate matching function takes the form

$$M = m\left(U^S + U^L, V, \frac{U^L}{U^S + U^L}\right) \quad (14)$$

where the last variable included should have a negative impact on the matching rate. This prediction is confirmed by Simon Burgess (1993) for Britain, Karen Mumford and Peter Smith (1997) for Australia, and Una-Louise Bell (1997) for Britain, France, and Spain. The specification adopted by Layard et al. (1991) is similar to the one in (14) but with the alternative measure of long-term unemployment described above.

Blanchard and Diamond (1989, 1990b) estimate a matching function for the United States over the period 1968–81. The estimated equation is a log-linear specification in levels:

$$\ln M_t = \alpha_0 + \alpha_1 \ln U_t + \alpha_2 \ln V_t + \alpha_3 t, \quad (15)$$

where the log of monthly national hirings is used as the dependent variable, unemployment is interpreted as a proxy for all job seekers (including employed and out-of-the-labor force) and the vacancy series was constructed from the help-wanted index. The estimated elasticities of matches with respect to vacancies and unemployment are positive and significant, and the time trend generally comes in with a negative and significant coefficient (but smaller than in Britain or other large European countries), implying a deterioration in the matching effectiveness of the labor market since the late 1960s. They find clear evidence of the existence of an aggregate matching function with constant or mildly increasing returns to scale, unit elasticity of substitution, and weights of 0.4 and 0.6 on unemployment and vacancies respectively. But the weight 0.4 is found when the unemployment rate is used as a proxy for all job seekers, which may not be appropriate when the number of employed job seekers is pro-cyclical; when the left-hand side variable is restricted to include only job matches from unemployment, the weight on unemployment rises to 0.6.

The higher unemployment elasticity of matching found in the British studies can be the result of the different dependent variable used. Pissarides (1986) and Layard et al. (1991) use the total outflow from unemployment whereas Blanchard and Diamond (1989, 1990b) construct a flow variable that approximates the total number of hires (including job-to-job moves and flows from inactivity directly into employment, a point that is not relevant here but addressed in the next section). Burda and Wyplosz (1994), who estimate log-linear matching functions for France, Germany, and the United Kingdom by

¹¹ The way that we formalized the ranking idea in equation (9) does not justify the claim made in the text about average matching rates. Ranking affects only the distribution of matches across the unemployed. But the frequently made assumption that the long-term unemployed reduce their search intensity or lose their skills would justify it.

regressing total exits from unemployment on vacancy and unemployment stocks, also found high elasticities of matches with respect to unemployment, in the range 0.5–0.7.

To see more formally our point, let X denote total exits from unemployment and M denote total hires, again from unemployment. Let also D denote exits from unemployment to out-of-the-labor force, a combination of “discouraged” worker effects, early retirement and going back to school. Let M be a log-linear constant returns to scale function of the type estimated by Blanchard and Diamond and D depend on vacancies with elasticity $-\alpha$ and on unemployment with elasticity β . If the tightness of the market V/U is a good measure of the cycle (as it is likely to be under constant returns; see Pissarides 2000), and movements from unemployment to inactivity depend only on the cycle, we expect $\alpha = \beta$. But if the experience of unemployment has additional influences on retirement and dropping out, we should expect on a priori grounds $\beta \geq \alpha$. The function estimated by the European studies is (with constants omitted)

$$X = M + D \\ = U^\eta V^{1-\eta} + U^\beta V^{-\alpha}. \quad (16)$$

Studies that use a measure of M in their regressions estimate η directly. Blanchard and Diamond’s estimate for this number is 0.6 and similar estimates (in the range 0.55–0.70) are found by Jan van Ours (1995), Tito Boeri and Burda (1996), and Burda and Stefan Profit (1996) for other countries.

Studies that use X as dependent variable in a log-linear regression approximately estimate

$$\frac{\partial X}{\partial U} \frac{U}{X} = \eta \frac{M}{X} + \beta \frac{D}{X} \\ = \eta + (\beta - \eta) \frac{D}{X} \quad (17)$$

and

$$\frac{\partial X}{\partial V} \frac{V}{X} = (1 - \eta) \frac{M}{X} - \alpha \frac{D}{X} \\ = 1 - \eta - (1 - \eta + \alpha) \frac{D}{X}. \quad (18)$$

The elasticity estimate obtained by studies that use the total exit as dependent variable should be lower for vacancies and, if $\beta > \eta$, higher for unemployment. Moreover, given that both sets of studies find constant returns to scale, the parameters must be such that

$$\beta = 1 + \alpha. \quad (19)$$

This necessarily implies that $\beta > \alpha$, that is, the experience of unemployment has an independent influence on dropping out of the labor force, in addition to its cyclical influence.

Blanchard’s and Diamond’s estimate of 0.6 for η , the Pissarides–Layard et al. estimate of 0.7 for the unemployment elasticity of total exits, and a plausible mean value for the ratio D/X (the fraction of unemployment exits that leave the labor force) of 0.4¹² give $\beta = 0.85$ and a negative value for α . These numbers, however, are derived from the difference between a point estimate of 0.6 and one of 0.7 and they are sensitive to small changes in these estimates. Given the estimates, a useful approximation that is well within the confidence interval of the elasticity estimates is one where $\alpha = 0$, i.e., one with implied total exit from unemployment of

$$X = U^\eta V^{1-\eta} + \gamma U, \quad \eta, \gamma \in (0, 1). \quad (20)$$

Blanchard and Diamond (1989, 1990b) also estimate equation (15) for the U.S. manufacturing sector alone. The results that they obtain in this case are broadly consistent with the aggregate ones, with the important qualification that the manufacturing matching function displays increasing rather than constant

¹²This is obtained from the data on worker flows reported by Burda and Wyplosz (1994).

returns to scale. The estimated sum of the elasticity of matches with respect to vacancies and unemployment is now 1.4 (see table 3). Estimates for U.S. manufacturing are also reported by Ronald Warren (1996), who estimates a more flexible translog function for all manufacturing for 1969–73, when a vacancy series for this sector was available. The translog specification gives a more accurate estimate of the returns to scale of a technology than the Cobb-Douglas form (see David Guilkey, C. A. Knox Lovell, and Robin Sickles 1983). The dependent variable in Warren’s study is total hires in manufacturing and the unemployment variable consists of all those currently unemployed who previously held jobs in the manufacturing sector. The correspondence of the flow variable that is used as dependent variable with the stock on the right-hand side is poor, but almost inevitable when hires in only one sector are used. He finds statistically significant increasing returns to scale with sum of coefficients on vacancies and unemployment of 1.33. Similar results are found by Yashiv (2000), on both a log-linear and a translog matching function for the whole Israeli economy over the period 1975–89. The estimated returns to scale in his matching function lie in the range 1.20–1.36.

The other studies summarized in table 1 generally confirm the results of the earlier studies discussed in this section for different countries and time periods.

4.3 Sectoral Studies

The difficulty with making inferences about labor market matching from aggregate time series beyond the initial results of the studies discussed in the preceding section led many authors to switch to more disaggregate specifications, either in panel or single cross-sections. Table 2 summarizes results for a number of sectoral studies.

Anderson and Burgess (2000) estimate a state-industry panel for the United States over the period 1978–84, using a similar specification to Blanchard and Diamond’s (1989) aggregate study. They also include variables for sex and age composition of the labor force and the degree of unionization, and distinguish new hires by origin, namely whether they come from employment or non-employment. Although the sum of estimated elasticities is well above one when hires from employment are used as the dependent variable, in neither case can the constant returns hypothesis be rejected at the conventional significance levels.

In an attempt to apply the matching function analysis to local labor markets, Melvyn Coles and Eric Smith (1996) and Robert Bennet and Ricardo Pinto (1994) both provide cross-section estimates of the matching function for local labor markets in Britain. Local labor markets are represented in Coles and Smith (1996) by travel-to-work areas. They use data for 257 areas in 1987 and estimate a regression for total hirings. As in the U.S. studies they find an elasticity of 0.7 on vacancies and 0.3 on unemployment. Their study also shows the importance of the geographic density of unemployment and vacancies in the hiring process, with more concentrated labor markets having higher matching rates. The analysis of Bennet and Pinto (1994) uses instead data from Training and Enterprise Councils, estimating a time series for each (Britain is divided into about 100 such areas). They find that the parameters of the matching technology do not vary substantially across districts, the elasticities being within a narrow range of 0.5 for both unemployment and vacancies, and therefore confirm that there are no serious problems of aggregation.

The Coles–Smith and the Bennet–Pinto studies treat local labor markets

as isolated marketplaces. Interactions among neighboring districts are modeled by Burda and Profit (1996), Burgess and Profit (1998), and Petrongolo and Étienne Wasmer (1999), who find evidence of matching spillovers across space but with smaller coefficients for neighboring districts. This finding highlights the importance of moving costs in matching and is consistent with Coles and Smith's finding that population density matters in local matching rates. We take up the issue of spatial aggregation below.

Most of the available evidence on matching functions at the sectoral level is based on log-linear specifications. A notable exception is the work by München, Svejnar, and Terrell (1999), who estimate a translog matching function on 76 Czech and 38 Slovak districts, which includes, apart from vacancies and unemployment, a number of local economic and demographic indicators. They test and reject both the Cobb-Douglas and constant returns restrictions for both countries. They find that both the elasticity estimates and the return to scale parameters vary over time and between the two sets of regions, with the Czech Republic showing a more dynamic, increasing returns economy and Slovakia starting off with a weak matching process, characterized by diminishing returns, but picking up to reach increasing returns by 1994. The study by München et al. (1999), and other studies summarized by Svejnar (1999), make a new use of the matching function, to study the labor market responses to the transition shocks in central and eastern Europe.

4.4 *Micro Studies*

The estimation of re-employment probabilities for unemployed individuals has the potential of distinguishing

between the determinants of the probability of receiving a job offer and that of accepting it. The former depends on the set of characteristics that influence a worker's productivity (such as age, education, and experience) and on local labor demand conditions, which is the effect captured by aggregate matching functions. The second probability depends on a worker's reservation wage, and therefore on the expected distribution of wages, the cost of search, unemployment income, and the probability of receiving a job offer.

Structural studies (see Nicholas Kiefer and George Neumann 1979a,b, 1981; Christopher Flinn and James Heckman 1982; Wiji Narendranathan and Stephen Nickell 1985; Kenneth Wolpin 1987; and Zvi Eckstein and Wolpin 1995) identify separately an accepted wage equation and a wage offer equation, and so they can distinguish between the determinants of each of these probabilities. Reduced-form or hazard function studies estimate instead the factors affecting the product of the two probabilities, namely the transition of workers from unemployment to employment, and are therefore more directly comparable with matching function studies.

Despite this connection, however, micro studies have not been used in the empirical search literature to make inferences about the properties of the aggregate matching function, with very few exceptions. Their contribution can be twofold. Micro studies control for a number of individual characteristics which can be aggregated to give shift variables in the aggregate matching function besides U and V . They can also be used to test for the effect of local labor market conditions on re-employment probabilities and from there aggregate to make inferences about the influence of local conditions on aggregate matching.

The early study by Tony Lancaster

(1979) uses a sample of British unskilled male workers to show that exit rates from unemployment are negatively affected by age, the duration of search, and the local unemployment rate. The age effect in the job-finding hazard implies that the age composition of the labor force should play a role in aggregate matching function estimates, with a younger pool of job-seekers delivering higher exit rates from unemployment (see for example Coles and Smith 1996, and Anderson and Burgess 2000). Negative duration dependence in job search implies that the incidence of long-term unemployment should reduce the unemployment outflow in aggregate specifications, which is confirmed by, among others, Layard et al. (1991) and Burgess (1993). Finally, the negative effect of unemployment captures the congestion effect of a larger pool of job-seekers on individual job-finding rates. This should translate into an aggregate elasticity of matches with respect to unemployment less than 1, which is the case in all aggregate studies.

Following Lancaster's application of duration models to re-employment probabilities, a large number of papers have studied the determinants of exit rates from unemployment, looking at a variety of specifications and control variables.¹³ Perhaps surprisingly, a result that frequently appears in the micro studies but not in aggregate studies is the influence of the unemployment insurance system (see Nickell 1979, and Narendranathan, Nickell, and Stern 1985). Although there are dissenting voices (e.g. Anthony Atkinson, Joanna Gomulka, John Micklewright, and

Nicholas Rau 1984), on balance micro studies find a (small) influence of unemployment insurance on re-employment probabilities. Aggregate studies have failed to find a robust effect, perhaps because of the complexity of the system and the difficulty of measuring accurately its dimensions in a time series. For example, it has been claimed that the duration of unemployment benefits is the most important dimension of the system that influences matching. But because there is very little time-series variation in the duration of entitlements, only cross-country data can be used to test for this effect. Yet, in cross-country regressions variations in durations are also limited, with some countries having unlimited durations and some restricting it to six or twelve months (see OECD 1994, and Pissarides 1999). Another dimension of the unemployment insurance system that has been emphasized in descriptive work is the leniency of the system. In a time series it is difficult to get a good measure of leniency.

When conditioning on the state of the local labor market, only a few micro studies (Nickell 1979; Atkinson et al. 1984; Maarten Lindeboom, van Ours, and Gusta Renes 1994; and Petrongolo 2001) take into account the demand side of the labor market and employers' search, by controlling for the local vacancy-to-unemployment ratio. A higher labor market tightness, represented by the V/U ratio, significantly increases the job-finding hazard in these studies, confirming the results of aggregate studies. Petrongolo (2001) also tests for the influence of the size of the local market on re-employment probabilities. Re-employment probabilities are conditioned on the number of unemployed workers and vacancies within the travel-to-work area of each worker. The coefficients on $\ln U_t$ and $\ln V_t$ are estimated

¹³ See Theresa Devine and Kiefer (1991) for a survey of hazard studies. Despite a rich literature on the study of unemployment exit rates, little work has been done so far on vacancy durations. Notable exceptions are van Ours and Geert Ridder (1992, 1993) and, more recently, Burdett and Elizabeth Cunningham (1998).

separately and found to be not significantly different from each other across a number of different specifications, which confirms constant returns to scale in matching.

Lindeboom et al. (1994) go one step further than the other studies, by making use of the link between the aggregate matching function and hazard rate specifications for evaluating the relative effectiveness of alternative search channels. They find that in the Netherlands employment offices are most effective in matching unemployed job seekers and vacancies, while newspaper advertisements are most effective in matching employed job-seekers and vacancies. Informal channels appear to be effective in both cases.

5. *Search On the Job and Out of the Labor Force*

A large number of job matches in modern labor markets are transitions from other jobs or directly from out of the labor force to employment. The former has an unambiguous theoretical interpretation: some employed workers are active job seekers. The latter is more vague. Since anyone without a job and actively searching for one is classified as unemployed, the workers who move directly from out of the labor force to employment are most likely the result of inadequate measuring, due for example to the length of time between survey points. A worker previously out of the labor force may become an active searcher and get a job within a week, and so miss the classification of unemployment in a monthly survey. In countries where labor force surveys are quarterly this problem can lead to large inflows of workers from out of the labor force to employment.

In principle, there is no difficulty introducing employment job seekers in the

models underlying the matching function (in theoretical work on matching, those out of the labor force who transit to employment directly do not have a separate status from the unemployed, as the period of analysis can be made sufficiently short to ensure that all those who enter employment pass first from the pool of job seekers). The way in which employed job seekers enter the matching function depends on the assumptions that one makes about their search behavior and its relation to that of the unemployed job seekers (Burgess 1993, Pissarides 1994). For example, if employers prefer employed job seekers to the unemployed, a ranking model could be used to arrive at (9), but with the number of employed job seekers taking the place of the short-term unemployed in the expression and the total number of unemployed workers ranking below them in the application queue.¹⁴ If, on the other hand, it is believed that the main difference between employed and unemployed job seekers is in the choice of search intensity or reservation wage, a function like (7) or (8) would be more appropriate. We derive the matching function (8) when there are employed job seekers as an illustration, under the reasonable assumption that employed job seekers have a different (usually higher) reservation wage than unemployed job seekers.

Let R_E be the mean reservation wage of employed job seekers and R_U the mean reservation wage of the unemployed. The number of unemployed seekers is, as before, U and the number of employed job seekers E . The number of job

¹⁴This would be the most appropriate framework for the analysis of "vacancy chains," whereby the employed take the new and better vacancies first, vacating jobs down the line, and the unemployed get pushed to the bottom of the vacancy chain. See Contini and Riccardo Revelli (1997) and George Akerlof, Andrew Rose, and Janet Yellen (1988).

vacancies is V and all workers qualify for all vacancies. If the unemployed search with intensity s and the employed with intensity normalized to unity, the contact technology is $m(sU + E, V)$ and the probability that an employed worker meets a job vacancy is $m(sU + E, V)/(sU + E)$. The probability that this vacancy is acceptable is $1 - G(R_E)$, so the hazard rate for the employed is $[1 - G(R_E)]m(sU + E, V)/(sU + E)$. The hazard rate for the unemployed satisfies a similar expression, $[1 - G(R_U)]sm(sU + E, V)/(sU + E)$. Therefore, the aggregate matching function is

$$M = \frac{[1 - G(R_E)]E + [1 - G(R_U)]sU}{E + sU} m(sU + E, V). \quad (21)$$

The introduction of employed job seekers opens up two empirical challenges, which are also relevant to the group of workers who in the data move directly from out of the labor force to employment. The first is the need to ensure a good match between the flow variable on the left-hand side of the equation and the stock variable on the right-hand side. We have already encountered this problem when we considered the implications of the group who flow from unemployment to out of the labor force and a similar measurement problem arises for those who flow from employment and out of the labor force to employment. The second challenge is partly one of theory. It is the question whether one can regress, say, job matches from unemployment on the unemployment stock, ignoring the employed job seekers and those out of the labor force. Are the estimates of the matching function elasticities obtained in this regression unbiased?

Before suggesting ways that the literature has dealt with these two questions, we summarize some evidence on the relative importance of employment

inflows that do not originate in recorded unemployment. Blanchard and Diamond (1989) construct a job-to-job flow series for the United States by making the assumption that these flows account for 40 percent of all job quits, the proportion estimated by Akerlof, Rose, and Yellen (1988), and that the quit rate for the economy as a whole is the same as the quit rate in manufacturing. This procedure leads them to conclude that job-to-job movements account on average for 15 percent of total hires in the period 1968–81. The remaining 85 percent is accounted for by hires from unemployment (45 percent) and hires from out of the labor force (40 percent).

Similar information for the United Kingdom can be derived from the Employment Audit, which uses the quarterly Labour Force Survey data. Job-to-job moves in 1992 represented 51 percent of total hires, while flows from unemployment and inactivity represented 21 percent and 27 percent respectively. Due to the three-month gap between observations, these data tend to overstate the importance of job-to-job moves and moves from out of the labor force, and understate those from unemployment, as many workers with less than three-month unemployment durations are missed in the unemployment count. Even allowing for some correction, however, Pissarides (1994) suggests a lower bound for job-to-job moves of 40 percent of total hires. Elsewhere in Europe, job switches appear to be less frequent than in the United Kingdom. Burda and Wyplosz (1994) estimate that in Germany in 1987, job-to-job flows represented 16 percent of employment inflows, with the rest being shared in equal proportions by unemployment and inactivity flows. The picture for German worker flows is thus similar to the U.S. picture. In France,

67 percent of the employment inflow was accounted for by unemployment outflows, with job-to-job flows accounting for a mere 10 percent and flows out of inactivity for 23 percent.

Thus both flows out of inactivity and job-to-job switches are large relative to the unemployment outflow. There is virtually no evidence on the properties of the flow from inactivity into jobs but some evidence on the properties of the job-to-job flow may shed light on its influence on the unemployment flow. What little evidence there is on the cyclical properties of flows in and out of inactivity gives mixed signals. Blanchard and Diamond (1989, 1990a) note that the flow of hires from out of the labor force is procyclical in the United States, while Burda and Wyplosz (1994) conclude that flows in and out of the labor force do not exhibit any particular cyclical pattern in Europe. A rich body of evidence, however, confirms that job-to-job flows are procyclical and closely linked to the quit rate.

Burgess (1993) builds a model of competition between employed and unemployed job seekers, and explains the procyclicity of job switches by modeling employed job search on the basis of a reservation wage rule. Employed workers whose wages fall below the (endogenous) reservation wage start searching for a better job. The reservation wage increases when the probability of receiving a job offer is higher, so, when the frequency of job offers rises in a boom, the employed have a stronger incentive to search, partially crowding out the unemployed from new jobs. In addition to this congestion effect, Pissarides (1994) argues that during a boom employers open vacancies that are more attractive to the employed, given that their proportion in the pool of job applicants rises, and destroy jobs that employed workers quit,

which are now acceptable only to the unemployed. This further enhances the procyclicity of job-to-job flows.

Recent empirical work explicitly takes into account employed job search and sometimes out-of-labor-force job search. Blanchard and Diamond (1989) use alternative definitions of the relevant pool of searchers, allowing the unemployed and those classified as inactive to be perfect substitutes up to a scalar level. They find that inactive workers do not enter the matching function with a significant coefficient.

For the United Kingdom, Burgess (1993) and Cliff Attfield and Burgess (1995) find evidence of endogenous job competition between employed and unemployed job seekers, obtaining an elasticity of the unemployment outflow with respect to total hires below 1. The standard matching function in U and V is then re-interpreted as a reduced-form relation for the unemployment outflow arising from the simultaneous determination of matching and job competition between employed and unemployed job-seekers, with on-the-job search being expressed as a function of the unemployment level. Boeri (1999) finds evidence of job competition between employed and unemployed job-seekers in a number of OECD countries, and concludes that the main competition for jobs for unemployed job seekers is due to job applicants who are employed in temporary jobs. Mumford and Smith (1997) use Australian data to extend the job competition to workers who are out of the labor force, and find evidence of inactive workers ranking below the unemployed, who in turn rank below the employed in the process of filling vacancies. No evidence of job competition is detected instead by van Ours (1995) for the Netherlands, finding that employed and unemployed workers mainly apply for different kinds of jobs.

It would appear from the literature discussed so far that data limitations make it difficult to ensure that the flow and stock variables in empirical matching functions refer to the same group of workers. The literature so far has not suggested a good alternative to collecting the relevant data. It has not explored the implications of omitting the job-to-job flow in a regression of the unemployment matching rate, given the well-documented procyclicality of that flow. Of course, if employed job seekers did not cause congestion for the unemployed because they applied to different kinds of jobs, as van Ours's (1995) work seems to imply, that would cause no problems in the estimation of the matching function for the unemployed. But suppose instead, for the sake of illustration, that the employed and unemployed apply to the same kinds of jobs and so congestion externalities are present. The simplest matching function in this case is $m(E + U, V)$, with the notation as before. The number of matches that go to unemployed workers is, on average, a fraction $U/(E + U)$ of the total, so the matching function for unemployed workers is

$$M_U = \frac{U}{E + U} m(E + U, V). \quad (22)$$

Let $m(E + U)$ in (22) satisfy the Cobb-Douglas restrictions with constant returns to scale and the elasticity with respect to job seekers equal to η , a number between 0 and 1. Then (22) becomes, after rearranging,

$$\ln M_U = (1 - \eta) \ln V - (1 - \eta) \ln(E + U) + \ln U, \quad (23)$$

where constants and other terms unrelated to U and V have been omitted.

This equation is, of course, simple to estimate, provided we have data for the stock of employed job seekers. Interestingly, we need such data even if our in-

terest is only in the unemployment flow, because of the congestion that the employed cause for the unemployed. An increase in the number of employed job seekers reduces the transition rate of the unemployed into new jobs. Yet, although equation (23) is of the type estimated by several authors, the number of employed job seekers, E , is not normally included among the regressors. The closest approximation to (23) can be found in Burgess (1993) for the United Kingdom, and Mumford and Smith (1997) for Australia. The specification estimated by Burgess regresses $\ln(M_U/U)$ on $\ln(M/L)$ and $\ln(U/L)$ (where M denotes total matches) and represents the reduced form equation stemming from a model of job competition between employed and unemployed job seekers, in which on-the-job search is a function of M/L and U/L . Mumford and Smith regress $\ln(M_U/U)$ on $\ln M$, $\ln U$ and $\ln(E/U)$, in which E is proxied by the number of job quitters in the previous period.

To see the implications of the omission of E from the list of regressors, suppose that the cycle is measured by the ratio V/U , the tightness of the labor market, and let $E = \lambda(V/U)^\alpha$. Given the responsiveness of the number of employed job seekers to the cycle, the coefficient α is positive and likely to exceed 1. If a log-linear form of (23) is estimated with $\ln V$ and $\ln U$ as independent variables, omitting E , the coefficients estimated are approximately the elasticities of matches, M_U , with respect to V and U evaluated at sample means. Let these be β_V and β_U respectively. Differentiation of (23) with $E = \lambda(V/U)^\alpha$ gives

$$\beta_V = (1 - \eta) \left(1 - \alpha \frac{E}{E + U} \right), \quad (24)$$

$$\beta_U = \eta + (1 - \eta)(1 + \alpha) \frac{E}{E + U}, \quad (25)$$

with $E/(E+U)$ evaluated at its sample mean.

Two implications follow from these expressions. First, the regression that omits E will give too low an estimate of the effect of vacancies on matchings and too high an estimate of the effect of unemployment, when compared with the underlying elasticity η . As a corollary, if the objective is to estimate the coefficient η , the estimate obtained from the estimated β s is biased upward. This is a direct implication of the procyclicality of employed job search, since if $\alpha = 0$, β_V gives an unbiased estimate of η . Second, if the matching function satisfies constant returns, as assumed, then a test of constant returns by comparing the coefficients β_V and β_U , as normally done in the literature, will reject constant returns in favor of increasing returns, since,

$$\beta_V + \beta_U = 1 + (1 - \eta) \frac{E}{E + U}. \quad (26)$$

Conversely, if constant returns is accepted on the β s, the underlying matching function with employed job seekers included satisfies decreasing returns to scale.¹⁵

6. Aggregation Issues

6.1 Time Aggregations

The matching function describes a process that takes place continually in spatially distinct locations. The use of discrete-time data for arbitrary regional divisions to estimate aggregate matching functions introduces both temporal and spatial aggregation problems.

Time aggregation problems arise when flow variables are estimated as

functions of stock conditioning variables. This happens in the empirical production literature, where a production function is used to describe the flow of output from the stocks of inputs. Similarly, the matching function describes the flow of matches as a function of the stocks of unemployment and vacancies. In order to analyze the problems introduced by time aggregation in this case, we consider for convenience an explicit log-linear version of the matching function and introduce a well-behaved disturbance term ε_t

$$\ln M_t = \alpha_0 + \alpha_1 \ln V_t + \alpha_2 \ln U_t + \varepsilon_t. \quad (27)$$

If M_t is measured as a flow over a time period, and U_t and V_t as stocks at some point during the period, U_t and V_t are depleted by matches M_t , and this generates a downward bias in the estimated coefficients α_1 and α_2 . This problem is often dealt with by using beginning-of-period stocks U_{t-1} and V_{t-1} as conditioning variables or as instruments for U_t and V_t . If there is no serial correlation in the disturbance term, the lagged stocks U_{t-1} and V_{t-1} are uncorrelated with ε_t and are therefore good instruments (Eli Berman 1997; Munich, Svejnar, and Terrell 1999). When there is serial correlation in the disturbances, authors have used as alternative instruments industrial production (Blanchard and Diamond 1990), GDP, world trade, and public deficit indexes (van Ours 1991).

But whatever stock variable is used on the right-hand side of the equation, the dependent variable is mismeasured, being the aggregated flow over a time interval during which the stocks change. The measured outflow over some time interval does not only include the outflow from the initial stocks, but also the outflow from the inflow over the same interval. For periods even as short as a quarter this can give rise to a situation

¹⁵Of course, it is also possible that the sum of the coefficients of both regressions falls within the confidence interval implied by constant returns, although their point estimates may differ in the direction pointed out.

in which the total outflow during the interval exceeds the initial stock. For vacancies, whose average completed duration is in most cases under a month, even monthly data would deliver exit rates above 1.

Here we discuss this problem more formally using an exponential probability distribution of duration, characterized by constant hazard with respect to duration during the measurement period. Assuming a hazard rate λ , the survival probability of an unemployed worker is $S_t = \exp(-\lambda t)$, with t denoting the elapsed duration of search. The probability of being matched (the outflow rate) over a time period of length t is therefore $F_t = 1 - \exp(-\lambda t)$.

Let us consider a period of unit length. Assuming an initial stock of unemployment U , and a subsequent inflow u_t , $t \in [0, 1]$, the unemployment outflow is given by

$$M = (1 - e^{-\lambda})U + \int_0^1 [1 - e^{-\lambda(1-t)}]u_t dt \quad (28)$$

where the first term denotes the outflow from the initial stock and the second denotes the outflow from the inflow. A symmetric expression can be computed for vacancies. Estimating (27) on discrete data using beginning-of-period stocks as conditioning variables therefore omits the originating stocks for the number of matches represented by the second term in (28).

Under the simplifying assumption of uniform inflow u during the whole period, (28) yields

$$M = (1 - e^{-\lambda})U + \left[1 - \frac{1}{\lambda}(1 - e^{-\lambda})\right]u. \quad (29)$$

It can be noted that the term in square brackets is bounded between zero and one and it is lower than the outflow from the initial stock, for the reason that the inflow has, on average, less time available for a successful match.

In order to take into account the

matches generated by inflows u and v , right-hand side variables in (27) should include the beginning-of-period stock, plus some proportion of the inflow. Given that each agent in u has a matching probability which is $(1 - e^{-\lambda})^{-1} - 1/\lambda$ times the matching probability of each agent in U , the pool of unemployed job seekers between time 0 and time 1 can be expressed in homogeneous “search units” as

$$U + \left[(1 - e^{-\lambda})^{-1} - \frac{1}{\lambda} \right] u, \quad (30)$$

and similarly for vacancies. In order to compute the expression in (30), the hazard rate λ can be obtained by estimating equation (29) on stocks and flows. Alternatively, for small enough λ , the term in square brackets in (30) can be approximated by $1/2$, using a second order Taylor expansion of $\exp(-\lambda)$ around $\lambda = 0$.

Gregg and Petrongolo (1997) follow the latter procedure in order to deal with the time aggregation problem in the estimation of an aggregate matching function for Britain for the period 1967–95. Their analysis combines this treatment of time aggregation with a stock–flow matching mechanism (see section 3.5). The resulting matching-function estimates suggest that there has been no deterioration in the matching effectiveness of vacancies over the period considered. There is evidence of some fall in the matching effectiveness of the unemployed, although less severe than that implied by the conventional stock-based analysis of matching (namely, the influence of the time trend of aggregate studies is reduced).

Berman (1997) uses instead the sum of beginning-of-period stocks and subsequent flows to construct a proper instrument for U_t and V_t in order to estimate a log-linear referral function for Israel over the period 1978–90. IV estimation delivers higher elasticities of

referrals with respect to unemployment and vacancies than OLS estimation, detecting a downward (simultaneity) bias in OLS estimates.

Burdett, Coles, and van Ours (1994) show that the use of beginning-of-period stocks as sole conditioning variables generates a bias in the resulting elasticities of M_t with respect to U_{t-1} and V_{t-1} that depends on the time series properties of the two stocks. Suppose that both U_{t-1} and V_{t-1} are mean-reverting series, an assumption which is implicit in a matching function where the number of matches is a positive function of U_{t-1} and V_{t-1} . In this case the average size of a stock over a time period tends to be negatively correlated with the size at the beginning of the period. This implies that, when unemployment (or the number of vacancies) is above the mean, the average size of the stock during the following period will be smaller, generating a smaller number of intra-period matches. On the other hand, when the initial stock is below the mean, its size tends to increase afterwards, generating a higher number of intra-period matches. This mechanism generates a downward bias in the estimated elasticities of M_t with respect to U_{t-1} and V_{t-1} .

It is shown, however, that for a small enough measuring interval, the size of the bias is approximately a linear function of its length. Thus the size of the bias can be estimated by doubling the length of the measuring interval and comparing the obtained coefficients with those estimated using the original data frequency. This procedure, applied by Burdett et al. to the data used by Blanchard and Diamond, suggests that the bias is not important whenever the data frequency is monthly or higher and the cycle frequency is yearly or higher.

An alternative way of ensuring matching probabilities strictly bounded be-

tween 0 and 1, proposed by Wouter den Haan, Gary Ramey, and Joel Watson (2000), departs from the standard log-linear specification (27). They consider that matching takes place when a firm and a worker meet through a pair-specific channel. There are J_t channels in the economy, and each agent is randomly assigned to one of them. With this procedure, a worker locates a vacancy with probability V_t/J_t , and a firm locates a worker with probability U_t/J_t . Matches are given by $M_t = U_t V_t / J_t$. The properties of this matching function depend on the specification of J_t . The specification adopted by the authors is $J_t = (U_t^l + V_t^l)^{1/l}$, which restricts exit rates of unemployment and vacancies between 0 and 1, as l goes from 0 to ∞ . Den Haan et al. use these functions in a dynamic general equilibrium model with productivity shocks. The calibration of their model delivers a close match with data on labor market flows when the parameter l is set equal to 1.27.

6.2 *Spatial Aggregation*

The other issue that links aggregate production and matching technologies is aggregation across space. As in the empirical production literature, most authors of empirical matching functions aggregate the number of unemployed workers and job vacancies across space and use the aggregates to explain the flow of job matches in the same space. This practice treats the aggregate economy as a single labor market, ignoring the fact that it might be a collection of spatially distinct labor markets with possibly little interaction. The relevant issue is whether aggregating local labor market data biases the resulting estimates. This issue is related to the one of "imbalance" in the distribution of unemployment and vacancies that we discussed in section 3.1.

Coles and Smith (1996) argue that spatial aggregation might bias the results towards constant returns to scale in the matching function, while the matching process could display increasing returns instead. The underlying intuition is that replicating a marketplace of a given size and with a given number of searchers should double the number of matches if there is no interaction between the two marketplaces. But if there is interaction, the number of matches more than doubles, because more cross-border matches can now be formed. So with interactions between markets, matches more than double when the number of searchers doubles within the original marketplace, implying increasing returns to scale. Since interactions are likely to be more common in more dense markets, Coles and Smith conclude that in estimation density is likely to be more important than market size, something for which they find evidence in their study. Indeed they find constant returns to scale on average but with more dense markets delivering higher matching rates for given size of the vacancy and unemployment pools.

Constant returns to scale are also not rejected in a similar study by Bennet and Pinto (1994), who estimate separate local matching functions over the period 1985–91 for 104 areas of Training and Enterprise Councils that cover Britain. They find that most of the estimates for the returns to scale range between 0.7 and 1.15.

A further issue concerns the interaction between local matching and regional migration or commuting behavior. The importance of job search considerations in worker migration is recognized by Jackman and Savouri (1992). They note that the direction of gross migration flows in Britain is consistent with a job search approach, in which

migration is interpreted as the outcome of job matching. The magnitude of migration flows is best explained in time series regressions by the evolution of the total number of job-worker matches. Regional migration facts are instead difficult to reconcile with the predictions of competitive human capital theory, mainly on the grounds that high wage regions do not seem to attract significant migration flows.

The effects of regional migration and commuting on local matching conditions are analyzed by Burda and Profit (1996). They represent an aggregate economy as a two-dimensional space divided into a number of districts. Workers' decisions determine search intensity in all districts, namely how many jobs to apply for in each district. This extension of the matching function to the spatial dimension relates job matching in a district to economic conditions everywhere in the economy, inducing a network of complex spillover effects between neighboring districts. Burda and Profit estimate a matching function that embodies regional spillovers for 76 Czech labor market districts, and find significant effects of neighboring unemployment on local matching. Constant returns to scale in the matching function cannot be rejected. This specification is also used by Burgess and Profit (1998) in order to study local matching and spillovers in 303 British travel-to-work areas. They find that more unemployed job-seekers (vacancies) in neighboring areas raise the local vacancy (unemployment) outflow but lower the local unemployment (vacancy) outflow.

Along similar lines, Petrongolo and Wasmer (1999) estimate a matching function for Britain (1986–95) and France (1983–94), using a regional panel for each country. Cross-regional spillovers are considered, allowing each worker to search in her own and other regions

with different search intensities. It is found that search intensity is positive and significant in regions that are adjacent to the one where the worker lives, although it is only about 10 percent of the level of search intensity in the region of residence. Constant returns to scale in the matching function are not rejected by either the British or the French data, in contrast to the aggregate study for France in table 3, which found decreasing returns.

In conclusion, although the problem of spatial aggregation has only recently been discussed in the estimation of matching functions, the findings of those who explicitly embody a spatial dimension into the estimation do not invalidate earlier results on aggregate matching functions. Their analysis, however, sheds more light on the regional dimensions of job matching and the spillovers between regions than aggregate studies that include aggregate measures of regional imbalance in unemployment and vacancy distributions.

7. *Conclusions*

Like most other aggregate functions in the macroeconomist's tool kit, the matching function is a black box: we have good intuition about its existence and properties but only some tentative ideas about its microfoundations. Yet, those tentative ideas have not been rigorously tested. They have been used only to provide justification for the inclusion or exclusion of variables from the estimation of aggregate or regional matching functions, leaving it to the empirical specification to come up with a convincing functional form.

The early aggregate studies converged on a Cobb-Douglas matching function with the flow of hires on the left-hand side and the stock of unemployment and job vacancies on the right-hand

side, satisfying constant returns to scale, and with the coefficient on unemployment in the range 0.5–0.7. In some of the estimates that use total hires as dependent variable (not only hires from unemployment) the coefficient on unemployment is lower, in the range 0.3–0.4, and the coefficient on vacancies correspondingly higher. But estimation of both Beveridge curves and aggregate matching functions points also to other variables that influence the simple Cobb-Douglas relationship. Much of the estimation of matching functions in the last decade has looked for those other variables and for better empirical specifications. Micro studies suggest as additional variables the age structure of the labor force, the geographical dispersion of job vacancies and unemployed workers, the incidence of long-term unemployment (exceeding one year), and unemployment insurance; interestingly, however, although the other variables have been found significant where tested, unemployment insurance has not been identified as a significant influence on aggregate matching rates. We have argued that this may be related to measurement problems and the difficulty of getting reliable time series data for the generosity of unemployment insurance systems.

Recent empirical work has used disaggregate data and modeled the micro matching functions more carefully, paying attention to the issue of consistency between the timing of the flows and the timing of the stocks in the regressions, the regional spillovers in matching, and the consistency between the flow and stock variables, given the observation that many matches involve either employed workers or workers classified as out of the labor force. The precision of the estimation has increased and the relation between hazard function estimation and aggregate matching function

estimation has become clearer. It has been found that aggregation problems have played a role in some of the shifts in the aggregate matching function, though not to an extent that can render the aggregate function “unstable.” Despite all the refinements and detailed tests, the findings of the first aggregate studies have not been challenged: the stable, constant returns aggregate function used in macroeconomic modeling finds strong support in the data of virtually all modern economies where tests have been conducted.

Future work needs to elaborate a number of issues. The search for microfoundations needs to continue, and rigorous tests of plausible alternatives done. Good microfoundations can aid the estimation of structural coefficients, which are used in model calibrations and policy analysis. Currently, the most popular functional form, Cobb-Douglas with constant returns to scale, is driven by its empirical success and lacks microfoundations. The most popular microeconomic models, such as the urn-ball game, do not perform as well empirically. Yet, different microeconomic matching mechanisms have different implications for wage determination and other types of behavior in markets with frictions, and can help in the design of optimal policy toward unemployment and inequality.

On the empirical side, on-the-job search and search out of the labor force need to be more carefully measured and their implications for unemployed search and matching studied. The meaning of constant returns also needs to be studied further. Although constant returns in the numbers involved in matching are supported, there have been no rigorous tests of the plausible property that the quality of matches is better in larger markets, on the grounds that participants have more choices. This

may be more true in skilled labor markets, where skill heterogeneities are more likely to matter, opening up the possibility of different matching technologies for different types of skill.

Appendix: Some History

What is the history of the matching function, and how did labor economists deal with frictions before the recent vintage of models?

Early writers on the economics of labor markets were aware of the importance of frictions but were unable to bring them into their formal models. John Hicks (1932) in the *Theory of Wages* devoted a chapter to unemployment. After introducing the “commonplace” definitions of unemployment, he made the claim that some kinds of unemployment induce wage changes and some do not; the ones that do not are “consistent with constant supply and demand for labor” and they make up “normal unemployment.” An important reason for the existence of normal unemployment, which is close to Edmund Phelps’s (1967) and Milton Friedman’s (1968) equilibrium or “natural” unemployment, is the fact that

although the industry as a whole is stationary, some firms in it will be closing down or contracting their sphere of operations, others will be arising or expanding to take their place. Some firms, then, will be dismissing, others taking on labor; and when they are not situated close together, so that knowledge of opportunities is imperfect, and transference is attended by all the difficulties of finding housing accommodation, and the uprooting and transplanting of social ties, it is not surprising that an interval of time elapses between dismissal and re-engagement, during which the workman is unemployed. (Hicks 1963, p. 45)

Moreover, he claimed that these costs, the frictions, are important in determining equilibrium wages, because they imply a range of indeterminacy due to monopoly rents. But more importantly, frictions according to Hicks (1963, ch. 4), slow down the response of (real) wages to shocks and so are a major cause of short-run disequilibrium in the labor market.

William Hutt (1939) also emphasized the importance of frictions in modern labor markets. In his *Theory of Idle Resources* he attempted to distinguish various supply-side reasons for unemployment, in the hope that they would be brought into the demand-side models of Maynard Keynes and others. Among them he included workers who are “actively searching for work” because they “judge that the search for a better opening is worth the risk of immediately foregone income.” He then argued that such individuals should not be counted as unemployed because they are working on their own account and doing the job that an employment agency would do “if the course of politics had allowed such an institution to emerge

in modern society" (Hutt 1939, p. 60). Ironically, these individuals are the only ones counted as unemployed according to modern definitions.

Hutt's plea to his contemporaries to take into account such causes of unemployment was ignored. The dominant view of unemployment that emerged from the depression of the 1930s was Keynes's view that the unemployment that Hicks called "normal" could be ignored. Keynes (1936, p. 6) defined some kinds of unemployment as compatible with "full employment" and uninteresting from his point of view, along similar lines to Hicks (1932) (though without crediting him). He called these kinds "frictional"—probably the first use of the term—and "between jobs," due to "various inexactness of adjustment which stand in the way of full employment." He also included "voluntary" unemployment to the kinds compatible with full employment. He credited Arthur Pigou (undated) for the best exposition of the "classical" view but criticized him for concentrating on real factors only and for claiming that only "frictional" unemployment will exist in equilibrium, and therefore "such unemployment as exists at any time is due wholly to the fact that changes in demand conditions are continually taking place and that frictional resistances prevent the appropriate wage adjustments from being made instantaneously" (Pigou's words, quoted by Keynes 1936, p. 278). Thus, like Hicks, Pigou blamed frictions mainly for slow (real) wage adjustments, a point which Keynes considered irrelevant, if not erroneous (Keynes 1936, p. 278), to the point that he called the title of Pigou's book, *Theory of Unemployment*, "something of a misnomer" (p. 275).

Keynes's followers replaced the slow real adjustment emphasized by Hicks and Pigou by slow nominal adjustment but did not attribute it to real frictions. Frictions reappeared in the literature some time later, and only after Phelps (1967) and Friedman (1968) reiterated Hicks's claims that in equilibrium there is some "normal" unemployment, which is independent of nominal factors, and which does not induce wage adjustments (see Phelps 1968, Mortensen 1970, Holt 1970a,b, and the Introduction and other contributions to Phelps et al. 1970). The frictions in Phelps's and Mortensen's models were summarized in a flow-of-labor function which depended on the firm's relative wage offer. (Of course, in competitive theory the elasticity of the flow-of-labor function to the individual firm is infinite.) The mechanism assumed by Phelps and Mortensen was similar to one of the mechanisms in modern "efficiency wage" theory, and the more recent work of Phelps (1994), as that of Steven Salop (1979), recasts that assumption more formally in an equilibrium framework with unemployment. Holt's papers are more in the tradition of older "structural" analyses (see, e.g. Christopher Dow and Louis Dicks-Mireaux 1958) and like the earlier analyses he assumes a relation between unemployment and job vacancies which implies scale economies in frictional equilibrium.

Early criticisms of the Phelps-Mortensen ap-

proach by Michael Rothschild (1973) and others, who demonstrated that the optimizing actions of agents in these models could not support the assumed wage distribution, and also Diamond's (1971) demonstration that in sequential search price will converge to the monopoly price, led to attempts to find reasons for the persistence of wage differentials in equilibrium.¹⁶ Successful user-friendly models with wage distributions for homogenous labor, however, did not appear in the literature until Burdett and Mortensen's (1998) demonstration that search models with wage posting could support wage distributions when workers search on the job.¹⁷ Jovanovic's (1979) model of job-specific productivity differences for ex ante homogenous labor could also be used to derive wage distributions in equilibrium search models. But the main impetus for new theoretical work in search theory came from the failure of neoclassical models of the labor market to explain wage and employment fluctuations and from the realization that there are large flows of jobs and workers in modern labor markets that could provide the building blocks for alternative models.¹⁸

The "matching function" was the key concept in the new generation of models. Although something resembling it was present in several earlier models,¹⁹ models that used it to simplify the

¹⁶The equilibrium model of Robert Lucas and Edward Prescott (1974), although innovative, was difficult to merge with mainstream analysis. The debt that it owes to the ideas in the Phelps volume is obvious, with its island equilibrium and the slow mobility across the islands, but its assumption that each island is in competitive equilibrium is very different from the "non-Walrasian" ideas in the Phelps volume. Both the model and the subsequent empirical implementation by Lilien (1982) inspired a lot of work but eventually the framework used to test Lilien's "sectoral shifts" hypothesis became more akin to search and matching models.

¹⁷Precursors to this model appeared earlier in response to Diamond's (1971) monopoly price demonstration. See Burdett and Kenneth Judd (1983). More generally, the condition for the existence of a wage distribution is that workers should have access to more than one wage offer at the same time. Lang (1991) and Montgomery (1991) who discuss wage inequality in the context of search models by making similar assumptions.

¹⁸For early studies of empirical flows see Robert Hall (1972), Martin Feldstein (1973), Stephen Marston (1976) and Kim Clark and Lawrence Summers (1979). Later, the work of Jonathan Leonard (1987), Timothy Dunne, Mark Roberts, and Larry Samuelson (1989), Davis et al. (1996), Blanchard and Diamond (1990a) and others provided new stimulus to theoretical developments.

¹⁹Notable early models with something akin to a matching function include the Phelps (1968), Mortensen (1970), and Holt (1970b) papers in the

characterization of equilibrium, by doing away with the wage distribution and the explicit modeling of the search decision, first appeared in the literature in the late 1970s. Butters (1977) described a process of the urn-ball type by which sellers let buyers know of their prices by posting advertisements at random in their mailboxes. Hall (1979) used this example to describe how recruiting firms select workers out of a homogenous unemployment pool, and derived an explicit functional form for the “job-finding rate.” Pissarides (1979) derived the same functional form and combined it with a general constant-returns-to-scale “job matchings function,” to describe the search and matching outcomes when there are two methods of search. Diamond and Eric Maskin (1979) assumed that meetings in a frictional market are governed by a “search technology,” which can be approximated by linear or quadratic functions. Roger Bowden (1980) examined vacancy-unemployment dynamics in search markets by making use of an “engagements function” that is linear-homogenous in the participating vacancies and unemployed workers. Interestingly, he gave as example the Cobb-Douglas form, with the constant measuring the efficiency of matching. The equilibrium models that influenced subsequent developments appeared soon after these authors demonstrated the usefulness of the concept of the matching function in capturing the effects of frictions on market outcomes.²⁰

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Phelps volume, Hansen (1970) and earlier mechanical models of the Phillips and Beveridge curves, such as Dow and Dicks-Mireaux (1958).

²⁰ For surveys of related literature see Mortensen and Pissarides (1999a,b) on the recent literature on search equilibrium, Mortensen (1986) on models up to 1984, and Devine and Kiefer (1991) on early empirical research in the context of search theory.

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