JOB DESTRUCTION AND PROPAGATION OF SHOCKS

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We develop and quantitatively implement a dynamic general equilibrium model with labor market matching and endogenous job destruction. The model produces a close match with data on job creation and destruction. Cyclical fluctuations in the job destruction rate serve to magnify the effects of productivity shocks on output, as well as making the effects much more persistent. Interactions between household savings decisions and separation decisions in employment relationships play a key role in propagating shocks.

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JOB DESTRUCTION AND PROPAGATION OF SHOCKS

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ABSTRACT. We develop and quantitatively implement a dynamic general equilibrium model with labor market matching and endogenous job destruction. The model produces a close match with data on job creation and destruction. Cyclical fluctuations in the job destruction rate serve to magnify the effects of productivity shocks on output, as well as making the effects much more persistent. Interactions between household savings decisions and separation decisions in employment relationships play a key role in propagating shocks.

1. INTRODUCTION

It has been well documented that the cyclical adjustment of labor input represents chiefly movement of workers into and out of employment, rather than adjustment of hours at given jobs. Thus, in understanding business cycles, it is centrally important to understand the formation and breakdown of employment relationships. The nature of employment adjustments over the cycle has also received close scrutiny. Evidence from a number of sources

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indicates that recessionary employment reductions are accounted for by elimination of pre-existing jobs, i.e. job destruction, to a greater extent than by diminished creation of new jobs. Substantial cyclical variation in the rate of job destruction suggests that closer consideration of the breakdown of employment relationships may help to explain how shocks to the economy generate large and persistent output fluctuations.[1]

This paper addresses these issues by studying the endogenous breakup of employment relationships in a dynamic general equilibrium model with labor market matching. Production is assumed to entail long-term relationships between workers and firms. We consider a version of Mortensen and Pissarides' (1994) model, where a worker and firm who are currently matched must decide each period whether to preserve or sever their relationship, based on their current-period productivity. By altering the tradeoff between match preservation and severance, aggregate productivity shocks induce fluctuations in the job destruction rate, thereby exerting effects on output that go beyond those resulting from productivity variations in continuing relationships.[2] We embed the basic Mortensen-Pissarides mecha-

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[1]For evidence on the importance of employment adjustment relative to hours adjustment, see Lilien and Hall (1986). Evidence on recessionary worker flows is provided by Blanchard and Diamond (1990), while Davis and Haltiwanger (1992) consider job flows in manufacturing. Corroborating evidence from Michigan data is provided by Foote (1995), who finds that for nearly all sectors, most of the recessionary employment adjustment in 1980 and 1982 can be accounted for by increased job destruction as opposed to reduced job creation.

[2]While we restrict attention in this paper to positive opportunity costs of employment as the source of incentives to break up employment relationships, it is important to recognize that breakups could also emerge from difficulties in writing labor contracts, as analyzed by Ramey and Watson (1997), where similar propagation effects would emerge. We focus here on opportunity costs for clarity and tractability. Further, we adopt a model in which productivity shocks are the sole source of macroeconomic fluctuations,

nism into a full dynamic general equilibrium model, assess its quantitative properties for macroeconomic aggregates as well as job flow data, and analyze the role of fluctuations in the job destruction rate in propagating shocks.

Parameters of the model are calibrated to labor market data, where measurements of worker and firm matching rates, as well as endogenous and exogenous separation rates, explicitly account for the observation that flows of workers out of employment relationships exceed flows of jobs out of firms. The calibrated model yields excellent matches between descriptive statistics from simulated data and measurements of job flows in manufacturing drawn from the Longitudinal Research Database (LRD). In particular, our model generates dynamic correlations of job creation, destruction and employment that closely fit those observed in the data: destruction tends to lead employment, creation lags employment, and creation and destruction exhibit high negative contemporaneous correlation. Moreover, negative recessionary shocks in the model cause job destruction to rise by a greater amount than job creation falls, so that most of the net employment reduction is accounted for by increased job destruction.

Most quantitative business cycle models in the RBC tradition share the feature that model-generated output data exhibit dynamic characteristics nearly identical to those of the underlying exogeneous shocks, so that economic mechanisms play a minimal role in propagating shocks (Cogley and Nason (1993,1995), Rotemberg and Woodford (1996)). In our model, however, fluctuations in the job destruction rate give rise to a significant propagation mechanism: productivity shocks are magnified in their effect on output at the point of impact, and the persistence of output effects is greatly increased. In simulated data, the

but propagation effects would operate similarly for other shocks that affected the returns to employment relationships.

standard deviation of output in our model is roughly two and one-half times larger than the standard deviation of the underlying driving process, reflecting both immediate magnification of shocks and slower adjustment of output following shocks. By way of comparison, the standard RBC model, as well as Hansen's (1985) indivisible labor variant, yield magnification ratios of less than two; further, nearly all of the magnification in the latter models occurs on impact, meaning that the models generate only slight amounts of persistence.[3]

In our model, productivity shocks are magnified because destruction of matches following a negative shock leads the capital stock to be spread over a smaller base of employment relationships. Due to declining marginal productivity of capital within employment relationships, capital is used less efficiently, so that output is reduced by more than the amount of the shock. Persistent output effects derive from interaction between household savings decisions and separation decisions in employment relationships: in response to a negative productivity shock, household dissaving puts upward pressure on the capital rental rate, which lowers the returns earned by active employment relationships and sharply increases the job destruction rate. This leads output to be even lower, and the implied wealth effect reinforces dissaving and spreads it out over time. In essence, recessionary dissaving puts added pressure on employment relationships, leading to even larger output reductions and more dissaving. As a consequence, negative shocks induce very large negative adjustments in the capital stock, spread over very long intervals. Interestingly, we find that apart from capital market effects, the need for gradual rematching of workers and firms following a rise in job destruction generates little persistence.

[3]As a further measure, we verify that our simulated data generate autocorrelations of output growth rates that match well the autocorrelations observed in U.S. data, reflecting the large amount of persistence generated by our propagation mechanism.

Propagation is also affected by the ease with which capital can be adjusted between employment relationships. To consider this issue, we develop a version of the model in which firms must choose their capital levels before they observe their idiosyncratic productivity shocks within the current period. Further, firms are assumed to have the right to sever their employment relationships and walk away from rental agreements if low idiosyncratic productivity is realized, and capital suppliers must wait until the following period before rerenting the capital to other firms. We show that propagation effects are significantly greater in the costly capital adjustment version of the model, because of the extra idle capital associated with increases in the job destruction rate. Thus, propagation of shocks is heavily influenced by costs of capital adjustment.

Several recent papers have considered labor market search and matching within a quantitative context. Merz (1995) and Andolfatto (1996) have implemented labor market matching models in the spirit of Pissarides (1985), where all job destruction is exogenous and the separation rates are constant over time. These papers demonstrate that incorporating matching improves the ability of the RBC framework to explain macroeconomic facts, including low variability of wages and productivity, and persistence of unemployment movements. Using our labor market measurements, however, we find that the implied propagation mechanism is much weaker when the job destruction rate is fixed, and further, models in this vein cannot account for the cyclical patterns of job creation and destruction. More recently, Cole and Rogerson (1996) have shown that a reduced form model inspired by Mortensen and Pissarides can do a good job explaining statistical regularities in the LRD, while Gomes, Greenwood and Rebelo (1997) have studied the ability of a simple search model incorporating endogenous separation to account for cyclical variability of the unemployment rate, the duration of unemployment spells, and flows into and out of unemployment.[4]

Our paper features some methodological advances relative to previous literature. We compute the job destruction rate as a fixed point within a dynamic general equilibrium exhibiting heterogeneity on the production side. Importantly, we do not rely on social planner solutions that restrict model parameters, in contrast to Merz (1995) and Andolfatto (1996). Further, we utilize a new specification of the labor market matching function that is motivated by search-theoretic considerations.

Section 2 describes the theoretical model. Measurement, calibration and numerical implementation issues are discussed in Section 3, and results are presented in Section 4. Section 5 evaluates the robustness of our propagation results to changes in parameter specifications, and Section 6 concludes.

2. Model

2.1. Employment Relationships. Employment relationships are taken to consist of two agents, a worker and a firm, who engage in production through discrete time until the relationship is severed. Individual employment relationships are indicated by subscript i. In each period t, firm i hires capital, denoted k_{it}. Output from production is given by $z_t a_{it} f(k_{it})$, where z_t represents a random aggregate productivity disturbance, a_{it} gives a random disturbance that is specific to relationship i, and $f(k_{it})$ is an increasing and strictly concave function. We assume that the relationship might be severed for exogenous reasons in any given period, in which case production does not take place. Let ρ^x indicate the

[4]While they consider a different class of models, Cogley and Nason (1995) and Burnside and Eichenbaum (1996) also emphasize that imperfections in the adjustment of labor input can play a role in propagating business cycle shocks.

probability of exogenous separation, assumed to be independent of z_t, a_{it} and of shocks realized in other relationships. In our benchmark model, the firm selects k_{it} after observing z_t, a_{it} and whether or not exogenous separation has occurred. Thus, capital may be freely adjusted in response to any shocks, either aggregate or idiosyncratic; we call this the case of *perfect capital adjustment* (PCA).

To assess the importance of capital adjustment costs in our model, we consider an alternative specification in which capital cannot be adjusted in response to idiosyncratic shocks. Thus, firm i chooses capital after z_t is observed, but before seeing either a_{it} or the exogeneous separation shock. We refer to this as the *costly capital adjustment* (CCA) case.

After observing all the shocks in period t, the worker and firm may choose to separate endogenously. If either exogenous or endogenous separation occurs, then there is no production in period t. In this event, the worker obtains a payoff of $b + w_{it}^w$ based on opportunities outside of the current relationship, where b indicates the worker's benefit obtained in the current period from being unemployed, and w_{it}^w denotes the expected present value of payoffs obtained in future periods. We take b to be exogenous. Due to free entry of firms into the worker-firm matching process, as described in the following subsection, the firm obtains a payoff of zero outside of the relationship.

Throughout most of the paper, we make the assumption that the idiosyncratic productivity shocks a_{it} are independently and identically distributed over time. This greatly simplifies the analysis of the model, as it eliminates the need to consider match-specific state variables for continuing relationships. The assumption of i.i.d. idiosyncratic shocks does run counter to the intuition often drawn from the Mortensen-Pissarides model, associating separations with persistent negative sectoral shocks requiring worker reallocation.[5] We show below, however, that persistence of idiosyncratic shocks is not needed to explain observed labor market flows, as we obtain excellent results under the assumption of i.i.d. shocks. Further, in Section 5 we demonstrate that our propagation results are robust to adding a significant persistent component to the process of idiosyncratic shocks, so that the assumption of i.i.d. shocks is not unduly restrictive.

Consider now the separation decision of the worker and firm in the PCA case. If the relationship is not severed, then production occurs and the worker and firm obtain the following joint payoff:

$$\max_{k_{it}} \left[z_t a_{it} f(k_{it}) - r_t k_{it}\right] + g_{it}, \tag{1}$$

where r_t is the rental rate of capital, and g_{it} gives the expected current value of future joint payoffs obtained from continuing the relationship into the following period.[6] Given any contingency that arises, the worker and firm bargain over the division of their maximized joint surplus. Negotiation is resolved according to the Nash bargaining solution, where π is the firm's bargaining weight. In particular, after observing productivity information, the worker and firm will choose whether or not to sever their relationship based on which option maximizes their surplus. Since the current period payoff becomes less attractive as a_{it} declines, it follows that there exists a level $\underline{a}_{it}$ such that the partners will opt for separation if $a_{it} < \underline{a}_{it}$, while the match will be preserved and production will occur if $a_{it} \geq \underline{a}_{it}$. The level of $\underline{a}_{it}$, referred to as the *job destruction margin*, is determined as follows:

[5] This intuition is discussed in detail by Davis, Haltiwanger and Schuh (1996, pp. 103-112).

[6] Observe that in (1) the firm chooses capital to maximize the joint returns of the worker and firm. In essence, the worker and firm are able to contract efficiently over the choice of capital.

$$\max_{k_{it}} \left[z_t \underline{a}_{it} f(k_{it}) - r_t k_{it} \right] + g_{it} = b + w_{it}^w. \tag{2}$$

where it should be recalled that the value of the firm's outside opportunities is zero. Associated with $\underline{a}_{it}$ is the *endogeneous separation rate* ρ_{it}^n:

$$\rho_{it}^n = \int_{-\infty}^{\underline{a}_{it}} d\mu(a_{it}), \tag{3}$$

where μ is the probability distribution over a_{it}. The endogeneous separation rate expresses the probability that a worker-firm match surviving the exogenous separation shock chooses to sever their relationship, based on their idiosyncratic productivity shock. Correspondingly, the overall separation rate is given by $\rho^x + (1-\rho^x)\rho_{it}^n$.

As for the CCA case, we assume that the firm may avoid making payments for capital if the relationship is severed, either exogenously or endogenously, i.e. the firm may declare bankruptcy in lieu of making payments. Thus, by renting capital the firm secures an option to utilize k_{it} units of capital, and the firm will exercise the option and pay the rental cost if productivity is sufficiently high. The value of $\underline{a}_{it}$ is now determined by:

$$z_t \underline{a}_{it} f(k_{it}^*) - r_t k_{it}^* + g_{it} = b + w_{it}^w, \tag{4}$$

where the firm's optimal choice of capital k_{it}^* solves the following problem:

$$\max_{k_{it}} \int_{\underline{a}_{it}}^{\infty} \left[z_t a_{it} f(k_{it}) - r_t k_{it} \right] d\mu(a_{it}), \tag{5}$$

Observe that in (5), the firm avoids making rental payments for realizations in the lower tail of the a_{it} distribution.[7]

[7] In (5) we implicitly assume that the firm cannot negotiate a lower capital rental payment in the event

2.2. Matching Market. Employment relationships are formed on a matching market. There is a continuum of workers in the economy, having unit mass, along with a continuum of potential firms having infinite mass. Let U_t denote the mass of unmatched workers seeking employment in period t, and let V_t denote the mass of firms that post vacancies. The matching process within a period takes place at the same time as production for that period, and workers and firms whose matches are severed can enter their respective matching pools and be rematched within the same period. All separated workers are assumed to reenter the unemployment pool, i.e., we abstract from workers' labor force participation decisions. Firms may choose whether or not to post vacancies, where posting entails a cost of c per period. Free entry by firms determines the size of the vacancy pool.

The flow of successful matches within a period is given by the matching function $m(U_t, V_t)$, which is increasing in its arguments and exhibits constant returns to scale. Workers and firms that are matched in period t begin active employment relationships, as described in the preceding subsection, at the start of period $t+1$, while unmatched workers remain in the worker matching pool.

2.3. Savings Decision. At the end of each period, following production and matching, output is allocated between consumption and capital for the following period. For simplicity, we assume that workers pool their incomes at the end of the period and make the savings decision in manner that maximizes the expected utility function of a representative worker, given by:

$$E_t[\Sigma_{s=t}^{\infty} \beta^{s-t} u(C_s)], \tag{6}$$

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that a_{it} is low. We discuss this restriction further in Section 2.3.

where β gives the discount factor, C_t indicates aggregate consumption and $u(C_t)$ is an increasing and strictly concave function.[8] Symmetry in consumption together with independence over time in the match-specific productivity shocks a_{it} allows us to suppress the i subscripts for the remainder of the paper.

The wealth constraint is determined as follows. Aggregate wage and profit income in period t is given by:

$$H_t = (1-\rho^x)N_t \int_{\underline{a}_t}^{\infty} [z_t a_t f(k_t^*) - r_t k_t^*]\, d\mu(a_t) - cV_t, \tag{7}$$

where N_t gives the mass of employment relationships at the start of the period, before any shocks have occured, and k_t^* indicates the capital level chosen by individual firms in period t.[9] Thus, wage and profit income consists of the payoffs generated in the current period by active employment relationships, net of total vacancy posting costs incurred by unmatched firms. Further, we interpret b as nontradable units of the consumption good that are produced at home by unemployed workers, so that aggregate home-produced output is $B_t = bU_t$. We assume that home-produced output cannot be used to generate capital.[10]

In the PCA case, rental payments are collected on all traded capital. Thus, rental income is given by $r_t K_t$, where K_t indicates the aggregate capital stock. Given that capital depreciates at rate δ per period, it follows that the wealth constraint for the PCA case is:

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[8]Merz (1995) and Andolfatto (1996) make a similar income-pooling assumption.

[9]Note that k_t^* will be a function of a_t in the PCA case, but not in the CCA case.

[10]The latter assumption implies the constraint $C_t \geq B_t$; it should be noted, however, that this constraint does not bind in any of the subsequent analysis. Home production in standard RBC settings has been considered by Benhabib, Rogerson and Wright (1991) and Greenwood and Hercowitz (1991). In contrast to these papers, our results do not rely on stochastic variability of the home production technology.

$$C_t + K_{t+1} = H_t + (r_t + 1 - \delta)K_t + B_t. \tag{8}$$

Note that total income in period t consists of wage, profit and capital income, which are equal to total market-produced output net of vacancy posting and depreciation costs, together with home-produced output.

In the CCA case, rental payments are collected only from firms whose relationships are not severed. We assume that capital that has been optioned to firms whose relationships are severed cannot be rented to other firms until the following period. Thus, adjustment of capital across relationships imposes a cost in the form of a one-period delay. The wealth constraint for this case is:

$$C_t + K_{t+1} = H_t + \left((1-\rho^x)(1-\rho_t^n)r_t + 1 - \delta\right) K_t + B_t, \tag{9}$$

Comparing (8) and (9), it may be seen that, in the CCA case, the household obtains a lower effective rental rate for given r_t.

Our notion of capital adjustment costs is motivated by the idea that renting capital to a firm involves a certain amount of commitment by the capital supplier, e.g. firms differ in their locations or engineering specifications, so that capital is not immediately transferable across firms. Further, firms are unable to commit contractually to making rental payments under future contingencies. When productivity turns out to be low ex post, the firm can walk away from the rental contract, and the supplier is left to bear the cost of idle capital for one period. The firm and household are also assumed to be unable to negotiate a lower rental payment in order to induce the firm to use the capital when productivity is low. Because renegotiation of capital contracts is suppressed, severance of employment relationships leads to added costs in the form of idle capital.

2.4. Equilibrium. An equilibrium of this model involves three components: (i) payoff-maximizing choices of capital rental k_t^* and job destruction margin $\underline{a}_t$ for each employment relationship, given the expected future payoffs w_t^w and g_t and the rental rate r_t; (ii) equilibrium determination of the expected future payoffs, given the payoff-maximizing choices and rental rate; and (iii) equilibrium in the capital market.

The conditions for payoff-maximizing k_t^* and $\underline{a}_t$ under the PCA case are given in (1) and (2), and under the CCA case in (4) and (5). Equilibrium values of the expected future payoff terms are determined as follows. Consider first the situation facing a worker and firm that are matched at the start of period $t+1$. If their relationship is severed in period $t+1$, then they obtain a joint payoff of $b + w_{t+1}^w$. If they avoid severance, then their relationship generates a surplus net of their outside joint payoff, which may be written as follows:

$$s_{t+1} = z_{t+1} a_{t+1} f(k_{t+1}^*) - r_{t+1} k_{t+1}^* + g_{t+1} - (b + w_{t+1}^w). \qquad (10)$$

The worker and firm bargain over this surplus, obtaining shares $1 - \pi$ and π, respectively. Division of the surplus is accomplished via transfer payments, e.g. the firm makes a wage payment to the worker.

Next, consider the situation of a worker in the period t unemployment pool. The worker obtains future payoffs of $b + w_{t+1}^w$ if he does not succeed in being matched in period t, or if he is successfully matched in period t, but the match is severed prior to production in period $t+1$. Alternatively, the worker receives a share of surplus from a productive relationship in period $t+1$, and thus obtains future payoffs of $(1-\pi)s_{t+1} + b + w_{t+1}^w$, if he is matched in period t and the match survives in period $t+1$. The worker's expected future payoffs, appropriately discounted, may therefore be written:

$$w_t^w = E_t\left[\frac{\beta u'(C_{t+1})}{u'(C_t)}\left(\lambda_t^w(1-\rho^x)\int_{\underline{a}_{t+1}}^{\infty}(1-\pi)s_{t+1}d\mu(a_{t+1})+b+w_{t+1}^w\right)\right], \tag{11}$$

where $\lambda_t^w = m(U_t, V_t)/U_t$ indicates the probability that the worker is successfully matched. Observe in (11) that the worker obtains $(1-\pi)s_{t+1}$ with probability $\lambda_t^w(1-\rho^x)(1-\rho_{t+1}^n)$, reflecting the event that the worker is matched in period t and the match survives in period $t+1$.

A firm in the period t vacancy pool, in contrast, must obtain a payoff of zero as a consequence of free entry. In particular, we have:

$$0 = -c + \lambda_t^f E_t\left[\frac{\beta u'(C_{t+1})}{u'(C_t)}(1-\rho^x)\int_{\underline{a}_{t+1}}^{\infty}\pi s_{t+1}d\mu(a_{t+1})\right], \tag{12}$$

where $\lambda_t^f = m(U_t, V_t)/V_t$ gives the firm's matching probability.[11] Finally, the expected future joint returns of a worker and firm who remain matched in period t are:

$$g_t = E_t\left[\frac{\beta u'(C_{t+1})}{u'(C_t)}\left((1-\rho^x)\int_{\underline{a}_{t+1}}^{\infty}s_{t+1}d\mu(a_{t+1})+b+w_{t+1}^w\right)\right]. \tag{13}$$

In contrast to (11) and (12), the partners in a continuing relationship do not need to be matched, so that they obtain the surplus s_{t+1} with probability $(1-\rho^x)(1-\rho_{t+1}^n)$.

It remains to consider the capital market. In the PCA case, the equilibrium r_t is determined by the following market clearing condition:

$$N_t(1-\rho^x)\int_{\underline{a}_t}^{\infty}k_t^* d\mu(a_t) = K_t. \tag{14}$$

[11] If the conditional expectation term in (12) lies below c at every level of V_t, then no firm would wish to post a vacancy and (12) would be replaced by $V_t = 0$.

The left-hand side of (14) indicates the demand for capital, consisting of the total number of employment relationships at the start of period t times the expected capital rental for each relationship. The capital market clears when capital demand is equal to the supply of capital in period t, given by K_t. In turn, K_{t+1} is determined by maximization of (6) subject to (8), for which the following is sufficient:

$$u'(C_t) = \beta E_t \left[u'(C_{t+1})(r_{t+1} + 1 - \delta)\right]. \tag{15}$$

As for the CCA case, (14) and (15) are replaced by:

$$N_t k_t^* = K_t, \tag{16}$$

$$u'(C_t) = \beta E_t \left[u'(C_{t+1})((1 - \rho^x)(1 - \rho_{t+1}^n)r_{t+1} + 1 - \delta)\right]. \tag{17}$$

Observe in (16) that each matched firm selects the same level of capital, reflecting the assumption that capital is chosen before idiosyncratic productivity shocks are observed. Correspondingly, expected rental payments per unit of capital in (17) are lower than r_{t+1}, since a proportion of firms will decline to make payments.

2.5. Summary. The workings of the model may be summarized as follows. The variables K_t and N_t are predetermined at the start of period t, where N_t indicates the stock of matched workers and firms as of the end of the preceding period. The timing of actions within a period may be broken down into three stages.

Stage 1. The disturbances z_t and a_t, as well as the exogenous separation shocks, are determined. Firms also rent capital, where the match-specific capital levels are selected either after all the shocks have been observed, or after only z_t has been observed, under the PCA and CCA cases, respectively.

Stage 2. The matched pairs that survive the productivity shocks engage in production, while unmatched workers and firms posting vacancies undergo the matching process.

Stage 3. Workers allocate the market-produced output between consumption and capital purchase.

3. Implementation

3.1. Separation and Matching Probabilities. We first discuss measurement of separation and matching probabilities used in calibrating the model. For measurement purposes, we derive these probabilities from relationships between stocks and flows arising in a deterministic steady state of the model. These may be regarded as average relationships over the long run. In measuring labor market flows, we begin with the observation that flows of workers out of employment relationships exceed flows of jobs out of firms; in other words, worker flows exceed job flows.[12] As a consequence, a substantial proportion of the firms that experience separations will desire to replace the lost workers, and will be successful at doing so, within the current period. We will need to account for firms' attempts to refill such job openings in our measurement of job flows.

Let N^s denote the steady state stock of employment relationships, and let U^s and V^s represent the per period flows of workers and firms, respectively, through the matching pools in the steady state. The probability of separation, for either exogenous or endogenous reasons, is indicated by ρ, so that ρN^s gives the total flow of workers and firms out of employment relationships within a given period. Note that $\rho = \rho^x + (1 - \rho^x)\rho^n$, where ρ^n gives the endogenous separation rate in the steady state.

Several direct measures of ρ are available. In surveying the empirical evidence, Hall (1995,

[12]See Davis, Haltiwanger and Schuh (1996, pp. 34-36).

p. 235) concludes that, for long-term employment relationships of the sort we consider, quarterly U.S. worker separation rates lie in the range of eight to ten percent. Using CPS data, Davis, Haltiwanger and Schuh (1996, p. 35) compute an annual separation rate of 36.8 percent, which works out to roughly 11 percent per quarter. From these estimates, we take 10 percent as our estimate of the quarterly steady state rate of exogenous and endogenous separation. That is, with periods in our model interpreted as quarters, we set $\rho = 0.10$.

To interpret exogenous and endogenous components of the separation rate, we make the assumption that firms experiencing exogenous separations attempt to refill the positions by posting vacancies in the ensuing matching phase, while firms having endogenous separations do not post vacancies. This assumption makes sense if exogenous separations are regarded as being worker-initiated, reflecting changes in the worker's personal circumstances. Such separations give rise to job vacancies that are reposted by the firm. Endogenous separations, in contrast, may reasonably be viewed as reflecting on the firm's circumstances, where firms would not attempt to rehire following such separations. It follows that the rate at which separations are reposted by firms, denoted by ω^f, will be equal to the proportion of all separations that are exogenous, or $\omega^f = \rho^x/0.10$.

We define job destruction and job creation in the following way. Period-to-period job destruction is recorded as total separations ρN^s less those job openings that are reposted and successfully refilled by firms within the period. The steady state mass of jobs destroyed per period is thus given by $\rho(1 - \omega^f \lambda^f)N^s$, where λ^f indicates the steady state matching probability for a firm. Job creation is recorded as the mass of firms who have no employees at the beginning of the period, but who find workers in the matching phase of the period. Therefore, $\lambda^f(V^s - \rho\omega^f N^s)$ is the mass of jobs created each period in the steady state. Note that a job is neither created nor destroyed by a firm that both loses and gains a worker in the same period.

We next impose the condition that the flow of jobs out of the stock of employment relationships must equal the flow of jobs into relationships, or job destruction must equal job creation, as required for a steady state. This condition may be written as follows:

$$\rho(1-\omega^f\lambda^f)N^s = \lambda^f(V^s - \rho\omega^f N^s). \tag{18}$$

Observe that this condition is equivalent to the steady state property that total separations equal total new matches, or $\rho N^s = \lambda^f V^s$.

Although the data is restricted to the manufacturing sector, the LRD evidence reported in Davis, Haltiwanger and Schuh (p. 19) allows us to pin down directly the job creation rate. From quarterly plant level data from U.S. manufacturing, 1972:2-88:4, we find the ratio of creation to employment to be:

$$\frac{\lambda^f(V^s - \rho\omega^f N^s)}{N^s} = .052. \tag{19}$$

Further, Davis, Haltiwanger and Schuh (p. 23) indicate that 72.3 percent of jobs counted as destroyed in a quarter fail to reappear in the following quarter, i.e. for plants experiencing employment reductions in a quarter, roughly three-quarters of the reduction persists into the following quarter. This implies:

$$\rho(1-\omega^f(\lambda^f + (1-\lambda^f)\lambda^f))N^s = .723\rho(1-\omega^f\lambda^f)N^s. \tag{20}$$

Combining (18), (19) and (20) yields $\lambda^f = .71$ and $\omega^f = .68$. Using our assumption that only exogenous separations are reposted, we then calculate $\rho^x = 0.068$. Correspondingly, the steady state endogenous separation rate is computed to be $\rho^n = 0.032$. It is worth noting that our finding of $\lambda^f = .71$ agrees with Ours and Ridder's (1992) result from Dutch survey data that 71 percent of vacancies reported in an initial survey were found to be filled in a follow-up survey roughly one quarter later.[13]

It remains to estimate the steady state matching probability for workers. Blanchard and Diamond (1990) use CPS data for 1968-86 to calculate an average stock of employed workers of 93.2 million. In abstracting from labor force participation decisions, we interpret unmatched workers in our model as including both workers classified as unemployed and those not in the labor force but stating that they "want a job," giving an average stock of unmatched workers of 11.2 million. Thus, the steady state ratio of unmatched to matched worker stocks is estimated to be 12 percent. In our model, we identify the mass of workers observed to be unemployed as $1 - N^s$, which equals $U^s - \rho N^s$ in the steady state. Note that this excludes workers with very short transitional terms of unemployment due to leaving one job and initiating another within the same period. The steady state condition for worker flows, corresponding to the job flow condition (18), may be written:

$$\rho(1 - \lambda^w)N^s = \lambda^w(U^s - \rho N^s), \tag{21}$$

which is equivalent to $\rho N^s = \lambda^w U^s$. Observe that all separated workers are assumed to enter the unemployment pool during the ensuing matching phase, i.e. the reposting rate for workers is unity. Combining (21) with our earlier findings $\rho = 0.10$ and $(U^s - \rho N^s)/N^s = 0.12$, we conclude that $\lambda^w = 0.45$ gives an appropriate estimate.

[13] As a further check on our estimates, we calculated that in the steady state, the estimates of ρ, λ^f and ω^f imply that 65 percent of the jobs destroyed in a quarter do not reappear in the second quarter following. This number is reasonably close to Davis, Haltiwanger and Schuh's (p. 23) corresponding figure of 59 percent.

3.2. Specification. We now turn to parameterization of the model. The following standard specifications of production and utility functions are adopted:

$$\begin{aligned} f(k_t) &= k_t^{\alpha}, \\ u(C_t) &= \frac{C_t^{1+\gamma}-1}{1+\gamma}. \end{aligned}$$

The aggregate productivity shock is determined by the process $\ln z_t = \xi \ln z_{t-1} + \epsilon_t$, where ϵ_t is taken to be i.i.d. normal with unit mean and standard deviation σ_ϵ. Further, we assume a_t is i.i.d. lognormal with unit mean and standard deviation σ_a.

In choosing the matching function, we depart from the standard Cobb-Douglas specification that has been used in the previous literature. Our new specification is motivated by considering how the matching technology operates on individual workers and firms. Imagine that J_t channels are set up to carry out matching within a given period. Each worker is assigned randomly to one of the channels, as is each firm. Agents assigned to the same channel are successfully matched, while the remaining agents are unmatched. With this procedure, a worker locates a firm with probability V_t/J_t, a firm locates a worker with probability U_t/J_t, and the total mass of matches is U_tV_t/J_t.

The number of channels J_t depends on the sizes of the unemployment and vacancy pools, reflecting thin market externalities. In particular, we adopt the specification $J_t = (U_t^l + V_t^l)^{1/l}$, from which we obtain the following matching function:

$$m(U_t, V_t) = \frac{U_tV_t}{(U_t^l + V_t^l)^{1/l}}. \tag{22}$$

Observe that the matching function is increasing in its arguments and satisfies constant returns to scale.[14]

3.3. Solution Procedure and Calibration. Solutions to the model are computed by expressing the equilibrium conditions in recursive form and calculating equilibria using the PEA-Collocation method, as discussed by Christiano and Fisher (1994); see the Appendix for details. In selecting parameter values, we make standard choices for the parameters α, δ, γ, β, ξ and σ_ϵ, as summarized in the first column of Table 1.[15] We give the worker and firm equal bargaining power by setting $\pi = 0.5$, and the choice of ρ^x is discussed in Section 3.1.[16] The remaining four parameters, l, b, c and σ_a, are selected to match statistics from simulated data to empirical measures of the endogenous separation rate and the worker and firm matching probabilities, derived in Section 3.1, along with a measure of the variability of employment relative to output, which in the simulated data is sensitive to the level of σ_a. Further, the parameters b, c and σ_a are varied between the PCA and CCA cases, as shown in Table 1.

The first three rows of Table 2 report separation and matching probabilities derived in Section 3.1, along with values computed from steady states of the model having determinis-

[14]A major advantage of our new matching function, relative to the Cobb-Douglas specification, is that the new function guarantees matching probabilities between zero and one for all U_t and V_t. In applying the Cobb-Douglas specification, truncation is necessary to rule out matching probabilities greater than unity. Such truncation can give rise to discontinuities that complicate obtaining accurate numerical solutions to the model.

[15]Hansen and Wright (1992), for example, make these selections in their analysis of labor market implications of RBC models. Although we cannot directly invoke factor share comparisons in our setting, the choice of $\alpha = 0.36$ does yield a quarterly output/capital ratio of roughly 10 percent in our simulated data, in line with U.S. evidence.

[16]Robustness of our propagation results to the choice of π is considered in Section 5.

tic aggregate productivity. The fourth row considers the ratio of the standard deviation of employment to the standard deviation of output, . We measure employment and output by converting monthly nonagricultural employment and industrial production for U.S. manufacturing, expressed on a per capita basis, into quarterly series starting at the middle month of each quarter for 1972:2-88:4, in line with the LRD employment measures. For the PCA and CCA models, this ratio is estimated using simulated data.[17] Actual and simulated data for this case are logged and HP filtered. As seen in Table 2, the simulated data produce good matches along the four dimensions considered.[18]

4. Results

4.1. Empirical Evaluation. Evaluation of the model's performance relative to U.S. aggregate data is given in Panel A of Table 3. Although both versions of the model perform well, the CCA model does a slightly better job explaining the observed volatility of output, as well as matching the empirical volatilities of consumption and investment, when compared to the PCA model.[19]

We next consider the ability of the model to account for characteristics of the LRD data. Consistent with our measurement procedure, as expressed in equation (18), we define rates

[17]In particular, we generate 100 simulated samples of 67 observations each, where initial conditions are randomized by ignoring the first 200 observations. This procedure is also used to generate model statistics in the tables below.

[18]In contrast to many quantitative studies, the complexity of the relationship between model parameters and statistics in our setting makes it difficult to obtain exact agreement between model and empirical statistics.

[19]It should be noted that measured consumption in the simulated data includes only consumption of market-produced output, in line with the empirical consumption data.

of job creation and destruction in the simulated data as follows:

$$\begin{aligned} cre_t &= \lambda_t^f (V_t - \rho^x N_t)/N_t, \\ des_t &= \rho_t - \rho^x \lambda_t^f, \end{aligned} \tag{23}$$

where ρ_t denotes the realized separation rate in period t. Thus, job creation is comprised of total matches in period t net of those matches serving to fill separations that are reposted within the period, while job destruction is given by total separations net of those that are refilled within the period.

Panel B of Table 3 compares volatilities of job creation and destruction relative to manufacturing employment in the in the LRD and simulated data. The chief discrepency between model and observation is that job creation is too volatile in the simulated data: creation is roughly eight times more volatile than employment in the PCA and CCA cases, versus less than five times in the LRD data.[20]

High volatility of creation can be accounted for by the fact that creation rates become very small in periods when V_t is low relative to $\rho^x N_t$, as seen in (23). In essence, the large number of reposted vacancies implied by our assumption that all exogenous separations are reposted may crowd out vacancies associated with job creation. To assess this effect, we alter our calibrated parameter by setting $\rho^x = 0.05$, in order to reduce the number of reposted vacancies, while adjusting other parameters to maintain an overall separation rate of 0.10. For the PCA model, this reparameterization gives $\sigma_{cre}/\sigma_N = 5.83$ and $\sigma_{des}/\sigma_N = 6.93$; thus,

[20]While our model does not produce the oft-discussed prediction that the volatility of destruction ought to exceed the volatility of creation, it should be noted that this prediction is distinct from the result that employment adjustment following recessionary shocks consists mostly of increases in job destruction rather than reductions in job creation. We show below that our model does generate the latter prediction.

reducing the amount of reposting lowers the volatility of creation. At the same time, the greater amount of endogenous separation raises the volatility of destruction.

Dynamic correlations between creation, destruction and manufacturing employment are presented in Table 4. In the LRD data, destruction tends to lead employment, in the sense that employment exhibits a large negative correlation with destruction lagged two quarters. Further, creation tends to lag employment. As may be observed in the table, the model displays remarkable agreement with the data, with signs and magnitudes of covariances being quite close. In particular, in both versions of the model, employment has a large negative correlation with past destruction and future creation. Further, the large negative contemporaneous correlation between creation and destruction is well matched by both the PCA and CCA models.

The cyclical variation in job creation and destruction implied by the model is illustrated in Figure 1, which shows impulse responses for a three standard deviation negative aggregate productivity shock in the PCA case. On impact, a large destruction spike is induced by an increase in the job destruction margin, accompanied by a smaller dip in creation, as firms post fewer vacancies in anticipation of lower future aggregate productivity. Thus, the model replicates the finding that recessionary employment reductions are accounted for by increases in job destruction to a greater extent than by reductions in job creation.

The induced increase in unemployment following the shock is sufficiently large to drive creation above its preshock levels in the period following the shock, as the higher matching probability for firms offsets the reduction in vacancies. This "echo effect" of destruction on creation, along with the simultaneous negative movements in creation and employment at the point of the shock, combine to generate the slight negative contemporaneous correlation between creation and employment. Further, the echo effect operates with a one period lag in the model, as opposed to a two period lag in the data, as the creation/destruction correlations indicate.

4.2. Propagation. A key issue in modelling business cycles is the manner in which underlying driving processes are amplified and spread out over time by economic factors captured in the model. As pointed out by Cogley and Nason (1993,1995) and Rotemberg and Woodford (1996), the intertemporal substitution mechanism embodied in the RBC model does a poor job propagating shocks, in that the characteristics of output series generated by the model closely mimic those of the underlying driving process. This property of the RBC model is strikingly at odds with the empirical observation of important differences between measured productivity and output.

Our model introduces cyclical variation of the job destruction rate as a new mechanism for propagating shocks through the economy. To clarify the discussion, we break down propagation effects into two categories. First, a productivity shock may be magnified in its effect on output within the period that the shock occurs, which we refer to as *impulse magnification*. Second, following the initial period, the output effect of the shock may die away more slowly than the effect on productivity, so that the shock has a more persistent effect on output. The combined effects of impulse magnification and persistence give rise to *total magnification* of the shock, reflecting the greater effect on output in all periods. We measure total magnification by the ratio of the standard deviation of output to the standard deviation of productivity.

Table 5 reports impulse and total magnification for the two versions of the model, as well as for a standard RBC model with variable hours and Hansen's (1985) indivisible labor model. Impulse magnification is obtained by comparing the output reduction associated with a three standard deviation negative productivity shock with the corresponding productivity reduction. All four models generate impulse magnification, in the sense that the output adjustment exceeds the reduction in productivity. Impulse magnification in the CCA model is larger than in the PCA model, due to the added negative effect of idle capital associated with severed relationships under CCA. The RBC and Hansen models generate impulse magnification that is roughly similar to the PCA and CCA models.

Total magnification in the PCA and CCA models is much larger than is impulse magnification, indicating that these models generate significant persistence. For unfiltered simulated data, total magnification is just under twice as large as impulse magnification in these models. For the PCA model, productivity shocks are magnified roughly two and one half times in their effect on output, while total magnification approaches three in the CCA model. The greater amounts of impulse and total magnification in the CCA model relative to the PCA model indicate the importance of capital adjustment costs for the propagation of shocks.[21] In contrast, impulse and total magnification are virtually the same in the RBC and Hansen models, indicating that persistence is nil.

Table 5 also reports total magnification for HP filtered simulated data. HP filtering has almost no effect with respect to the RBC and Hansen models, reflecting lack of persistent effects. However, some of the total magnification is removed by filtering the PCA and CCA models, although magnification remains significant. Removing low frequency variation gives a misleading picture of total magnification under the PCA and CCA models, since magnification continues to be important even at low frequencies.

[21]It should also be noted that idle capital imposes a high social cost in the CCA model. Moving from the CCA to the PCA model under the CCA parameters raises output and consumption by 21% each in the steady state.

These results are expressed graphically in Figure 2, which presents impulse responses for aggregate productivity together with output in the four models. In the RBC and Hansen models, the shock is magnified in the initial period, but thereafter output dynamics track the productivity dynamics very closely. Persistent output effects are vividly apparent for the PCA and CCA models, however, as the adjustment of output toward the steady state is much slower than the productivity adjustment.

The added persistence introduced by our model is helpful for explaining the autocorrelation structure observed in U.S. data. Figure 3 depicts the autocorrelations of output growth rates in U.S. GNP over the period 1961:1-93:4, together with corresponding autocorrelations for the growth rate of the aggregate productivity shock and output in the PCA, CCA and RBC models. The PCA and CCA models account for much of the difference between the GNP data and the productivity shock, especially in the first order autocorrelations, while the RBC model generates autocorrelations that are substantially equivalent to those of the shock.[22] Further, the PCA and CCA models yield positive second-order autocorrelations, which are qualitatively consistent with the data.

To assess the importance of cyclical variation in the job destruction rate for our findings, we consider an alternative version of the PCA model, in which all separations are exogenous. This is accomplished by setting $b = 0$ and $\rho^x = 0.10$; since home production is zero, workers and firms will never voluntarily sever their relationships, meaning that all separations are exogenous. Other parameters are recalibrated to obtain the worker and firm matching probabilities derived in Section 3.1. As seen in Figure 3, autocorrelations for this exogenous separation case represent a slight improvement over the RBC model, but are still far from

[22] Autocorrelations in the Hansen model are nearly identical to those in the RBC model.

those observed in the data.[23] Impulse responses for the exogenous separation and PCA models are compared in Figure 4. While the output effect of the shock in the exogenous separation case is slightly more persistent than the effect on productivity, impulse magnification is virtually nonexistent. As a consequence, output reductions remain small relative to the PCA model, and unfiltered total magnification is only 1.25. From this we conclude that fluctuations in the job destruction rate are central to producing the impulse magnification and persistence underlying our total magnification results.[24]

4.3. Sources of Propagation. The propagation mechanism embodied in our model serves both to magnify shocks on impact and to make their output effects more persistent. Impulse magnification derives from the fact that the rise in job destruction following a negative productivity shock will cause the capital stock to be spread over a smaller base of

[23]Our finding of little persistence in the exogeneous separation case may appear to conflict with results of Andolfatto (1996), who considers a DGE model with labor market matching and an exogeneous separation rate. Part of the difference is explained by the fact that, in calibrating his model, Andolfatto utilizes a quarterly worker matching probability of roughly 20 percent, which implies an unemployment duration of five quarters. Andolfatto obtains this measurement by including in the worker matching pool *all* adults that are out of the labor force, together with the unemployed. Resolving our exogeneous separation model with Andolfatto's worker matching probability yields a significant increase in persistence.

[24]It is interesting to note that our magnification results are not linked to counterfactually large wage variability. In our model, wages may be measured as bargaining transfers from the firm to the worker under the hypothesis that the firm appropriates the payoffs from an active employment relationship. In the PCA model, the standard deviation of this wage measure relative to the standard deviation of output is 0.30, and the contemporaneous correlation of wages and output is 0.83. Wage volatility and output correlation are smaller in our model relative to standard RBC models due to the fact that low productivity relationships experience separations in lieu of wage reductions.

employment relationships, leading the capital stock to be used less efficiently due to diminishing marginal productivity of capital within relationships. Thus, output is reduced by more than the decline in productivity, giving rise to impulse magnification in the PCA model. Additional output reduction occurs in the CCA model on account of the idle capital associated with separations. The extent of impulse magnification is tied to the variability of the idiosyncratic shock, which we measure by σ_a. As variability is reduced, the job destruction margin lies closer to mean productivity; the marginal employment relationship then has greater importance with respect to the efficiency of capital utilization, and magnification is correspondingly increased. In our calibration, we use the variability of employment relative to the variability of output to pin down σ_a, effectively determining the degree of magnification.

To understand the source of persistent output effects in our model, it is helpful to consider the nature of capital stock adjustment following a negative productivity shock. Figure 5 depicts impulse responses of capital in the PCA and RBC models for the negative productivity shock considered in the earlier figures. As may be observed, the capital reduction in response to the shock is much deeper and more prolonged in the PCA model, compared to the RBC model, suggesting that propagation in the PCA model is tied to the nature of capital adjustment. In addition, the figure shows the impulse response of capital in the exogenous separation model discussed at the end of Section 4.2. Capital reduction in the PCA model is also much greater than in the exogenous separation model, meaning that variation in the separation rate is important for generating large adjustments in the capital stock.

As the preceding comparison suggests, interaction between job destruction and capital adjustment serves greatly to prolong the output effects of a shock. To assess this interaction more closely, we consider a thought experiment in which the PCA model is hit with a negative aggregate productivity shock, but capital adjustment is suppressed by holding capital fixed at its steady state level. This allows the propagation mechanism to be decomposed into an output response occuring apart from capital adjustment, and an added response driven by capital adjustment.[25] The results of this exercise are shown in Figure 6. In moving from the productivity shock to the impulse response of output under fixed capital, magnification remains large in the immediate aftermath of the shock, but output effects die away relatively quickly, as seen in the figure. Importantly, the requirement that displaced workers be gradually rematched does not in inself generate significant persistence. As the figure makes clear, highly persistent output responses in the PCA model are traceable to the added effects of capital adjustment.[26]

Large capital adjustments are in turn accounted for by feedbacks between household savings decisions and separation decisions in employment relationships. Figure 6 further shows that capital adjustment in response to the negative shock raises the rental rate of capital in the PCA outcome, relative to the fixed capital outcome. Higher rental rates lead to lower returns in employment relationships, driving up the endogenous separation rate, as shown in Figure 7. This comparison reveals job destruction to be highly sensitive to the rental rate: in period 20, for example, moving from the fixed capital outcome to the

[25]To keep the discussion simple, we focus here on the effects of holding capital fixed at the original solution to the PCA model. Results are similar when the model is resolved with a fixed capital level, but to avoid additional details we do not consider that case here.

[26]The figure also depicts impulse responses of the capital rental rate, and it may be seen that, in the fixed capital case, the impulse responses of output and the rental rate, normalized by steady-state levels, are identical. This occurs because, under our specification of $f(k_t)$, output and the rental rate are proportional to each other when the capital stock is held fixed.

PCA outcome raises the rental rate by about one percent, while pushing up the endogenous separation rate by nearly nine percent.[27] The higher rate of job destruction reduces output based on less efficient use of the capital stock, and the implied wealth effect reinforces dissaving and spreads it out over time. In essence, dissaving in response to negative shocks puts added pressure on employment relationships, generating an output feedback that leads to even more dissaving.[28]

5. Robustness

In this section we assess the robustness of our propagation results to the specifications of the idiosyncratic productivity shocks and the bargaining share parameter. We first consider the effect of modifying our assumption of i.i.d. idiosyncratic shocks by introducing persistence. Let the production function now be given by $z_t a_{it} d_{it} f(k_{it})$, where d_{it} indicates the persistent component of idiosyncratic productivity and the other variables are defined as before. We adopt a very simple specification of the persistent component, where d_{it} may assume two possible values, and the realization of d_{it} for a particular employment relationship is determined once and for all when the match is first formed. The latter restriction serves to add a large amount of persistence, while making the extended model computationally tractable. The processes for z_t and a_{it} are specified as before.

The new production function is applied to the PCA model, parameterized as in Table

[27]The PCA outcome is further associated with a lower worker matching probability and a slightly higher household discount rate, relative to the fixed capital outcome, both of which would tend to lower the endogenous separation rate. Thus, the higher level of the endogenous separation rate in the PCA outcome is explained by the increase in the rental rate.

[28]It is interesting to note the impulse responses for savings rates are roughly similar in the RBC and PCA models. Thus, differences in savings behavior across the two models can be accounted for by wealth effects.

1, except that σ_a is lowered to 0.055 in order to generate the same volatility of HP filtered output as under the original parameterization. The possible values of d_{it} are 0.99 and 1.01, each realized with probability 0.5. This represents a very large persistent effect: the increase in the equilibrium value of a match drawing $d_{it} = 1.01$ versus $d_{it} = 0.99$ amounts to 28% of per capita output. For this version of the PCA model, total magnification becomes 2.43 for unfiltered data, and 1.70 for HP filtered data, which is essentially unchanged from the earlier results. Further, the model calibration remains good. We conclude that our propagation results do not depend on the assumption of i.i.d. idiosyncratic productivity shocks.

Introducing persistence has offsetting implications for magnification of shocks. On one hand, separations will be concentrated disproportionately among employment relationships having persistently low productivity, which tends to lower the output magnification associated with variations in the job destruction rate. On the other hand, introducing a persistent idiosyncratic component means that the variability of the i.i.d. component must be reduced in order to preserve the overall variability of output, which tends to raise magnification. In the preceding example these two effects cancel out.[29]

Finally, lowering the bargaining share parameter in the PCA model to 0.4, while keeping the other parameters fixed, gives unfiltered and HP filtered total magnification of 2.53 and 1.67, respectively, while the corresponding numbers are 2.31 and 1.67 when the share parameter is raised to 0.6. Thus, our propagation results are robust to alternative specifications of the share parameter.

[29] Our specification of persistent idiosyncratic shocks is admittedly rudimentary, and a broader inquiry into the role of persistence would be of interest. Any such inquiry would encounter significant computational hurdles associated with tracking idiosyncratic state variables over the range of possible persistent shocks.

6. Conclusion

In this paper we have established the quantitative importance of a macroeconomic propagation mechanism associated with cyclical fluctuations in the job destruction rate. Our theoretical model endogenizes the determination of the job destruction rate as part of a dynamic general equilibrium with labor market matching. The model is calibrated to data on worker and job flows, and our specification features a new matching function motivated by search-theoretic ideas. Our computation procedure does not rely on a social planner solution, allowing us to avoid restrictions on bargaining parameters that have been imposed in earlier work. Empirical support for the model is found in the good matches that it produces with U.S. data, particularly with respect to dynamic correlations of job creation, job destruction and employment in manufacturing.

In our model, aggregate productivity shocks are strongly magnified in their effects on output, both in the period of impact and in the periods following. Increased job destruction following a negative shock magnifies the output response because the capital stock is used less efficiently when it is spread over fewer employment relationships, and when job loss leads some capital to be idled. Further, large persistent effects emerge from the fact that household dissaving puts added pressure on employment relationships, by driving up the capital rental rate. Our results suggest that interactions between the capital and labor markets may be of central importance in propagating shocks. Further, policies that counteract the negative effects of recessionary dissaving, by restricting dissaving or strengthening employment relationships during recessionary episodes, have the potential to provide significant welfare benefits.

A useful extension of the current model would involve closer examination of the interactions between capital and labor adjustment. Recent work by Ramey and Shapiro (1997) has focussed on costs of reallocating capital across sectors. Incorporating these ideas into the current framework would make possible a rich synthetic analysis of factor adjustment. A further useful extension would incorporate noncontractible choices by the worker and firm, as considered by Ramey and Watson (1997), into the production process. Social costs of job loss would depend on the extent to which separation is driven by the attendant fragility of employment contracts, as opposed to positive returns to unemployment of the form analyzed in the present paper.

7. Appendix

7.1. Solution Algorithm and Accuracy.

In this section we discuss the solution algorithm used to solve the model. The equations of the model are first summarized, then the algorithm is spelled out, and finally the accuracy of the numerical solutions is assessed.

The Equations. The model consists of the following equations. The aggregate shock is given by:

$$\ln z_t = \xi \ln z_{t-1} + \epsilon_t, \epsilon_t \sim N(0, \sigma_\epsilon^2).$$

The relation-specific shock for match i is given by:

$$\ln a_{it} \sim N(0, \sigma_a^2). \tag{24}$$

Throughout the appendix, the i subscript denoting the particular match will be suppressed. At each point in time, however, there is a continuum of matches, and each match receives an independent draw from the distribution given in (24).

The discounted value of future joint benefits for a match that does not break up in period t is indicated by (13), while (11) shows the discounted value of future benefits obtaining to the worker when the match does break up in period t. The demand for capital by an individual firm in the PCA case derives from the following first-order condition for (1):

$$z_t a_t f'(k_t^*) = r_t. \tag{25}$$

In turn, the job destruction margin and capital market equilibrium are determined by (2) and (14). As for the CCA case, the job destruction margin and capital demand are jointly determined by (4) and the first-order condition for (5):

$$\int_{\underline{a}_t}^{\infty} [z_t a_t f'(k_t^*) - r_t] d\mu(a_t) = 0, \tag{26}$$

whereas (16) gives the capital market clearing condition. For given values of g_t, w_t^w and the three state variables K_t, N_t and z_t, the equations (25), (2) and (14) in the PCA case, or (26), (4) and (16) in the CCA case, can be solved for $\underline{a}_t$, r_t and k_t^*.

Labor market flows are determined as follows. Given the endogeneous job destruction rate (3), which depends on $\underline{a}_t$, the unemployment rate is given by:

$$U_t = 1 - (1 - \rho^x)(1 - \rho_t^n) N_t. \tag{27}$$

The level of vacancies V_t may be determined using the free-entry condition (12) for a given value of the conditional expectation, where firms' matching probability λ_t^f derives from the matching function (22) together with the unemployment rate given in (27). The separation rates and matching function determine the law of motion for employment:

$$N_{t+1} = (1 - \rho^x)(1 - \rho_t^n) N_t + m(U_t, V_t).$$

Finally, the representative household's budget constraint and intertemporal Euler equation are given by (8) and (15) in the PCA case, and (9) and (17) in the CCA case. For given values of the conditional expectation and state variables, the two equations in either case can be used to solve for C_t and K_{t+1}.

Solution Algorithm. We compute equilibria using the PEA-Collocation method; see Christiano and Fisher (1994) for discussion of this and related solution methods. The key to the algorithm is to replace the conditional expectations in equations (11), (12), (13) and (15) or (17) by second-order Chebyshev polynomials of the three state variables K_t, N_t and z_t. The tensor product method is used to build multidimensional basis functions from one-dimensional basis functions, which requires solving for 108 (=4*27) unknown coefficients. When the conditional expectations are replaced by their approximations and the coefficients of the polynomials are known, the equations listed in the preceding subsection can be used to solve the model at given values of the state variables.

In solving the system of equations with the conditional expectations replaced by known functions of the state variables, two issues require closer attention. First, to compute integrals of the form $\int_{\underline{a}_t}^{\infty} h(a_t) d\mu(a_t)$, global quadrature methods such as Hermite-Gaussian quadrature could be applied by extending the function $h(a_t)$ to take the value zero at values of a_t below $\underline{a}_t$. This method, however, compromises accuracy since the extended function is not differentiable at $\underline{a}_t$. To avoid this problem, we instead use Simpson quadrature, which is a local quadrature technique that makes it possible to set the lowest quadrature point equal to $\underline{a}_t$. Fifteen quadrature points are used, with the highest being equal to four times the standard deviation of a_t.

Second, the model contains nonlinear equations. For PCA, a nonlinear equation solver is needed to find the value of r_t at which the capital market clears, while for CCA, a nonlinear equation solver is needed to find the value of $\underline{a}_t$ at which the implied expected value of the marginal product of capital generates a rate of endogeneous separation equal to $\int_{-\infty}^{a_t} d\mu(a_t)$. Although numerical integration is involved in both cases, the functions are monotone and a simple bisection algorithm is capable of finding the solutions fairly quickly.

The values of the coefficients of the approximating polynomials are found using a simple iterative procedure. The procedure utilizes a three-dimensional grid of the state variables, where the roots of the Chebyshev polynomials are used as grid points. Therefore, for each polynomial we have as many grid points as unknown coefficients, and the approximating polynomials will be exactly equal to the conditional expectations at the grid points. Trial and error is used to find values for the lower and upper bounds that include most realizations in long simulations and at which a further increase in the range does not affect the results.

The procedure starts with a set of initial values for the coefficients of the Chebyshev polynomials. Replacing the conditional expectations in (11), (12), (13) and (15) or (17) with these polynomials yields a set of policy functions that can be used to solve for the endogeneous variables under any realization of the three state variables. Using these policy functions, we calculate conditional expectations at each gridpoint using numerical techniques. Since the integrands in (15) and (17) are smooth functions of the normally-distributed random variable ϵ_{t+1}, it suffices to use Hermite-Gaussian quadrature with five quadrature nodes.[30] For the remaining equations, the integrands in the conditional expectations are smooth functions of ϵ_{t+1} but not of a_{t+1}. To calculate these integrals, we use Hermite-Gaussian quadrature to integrate over ϵ_{t+1} and Simpson quadrature, as discussed above, to integrate over a_{t+1}.

At each grid point, the calculations consist of two parts. First, we solve for K_{t+1} and N_{t+1}. Second, the integrands are calculated at the different quadrature nodes of ϵ_{t+1} and

[30] Since ϵ_{t+1} is not distributed as a standard normal, we must apply a linear transformation of the variables and the appropriate adjustment of the Gauss-Hermite abscissas and weights (cf. Judd (1991)).

a_{t+1}. The conditional expectations are then computed as sums of these calculated values weighted by the quadrature weights.

New values for the coefficients of the Chebyshev polynomials are obtained by projecting the calculated values of the integrals onto the basis functions. The algorithm then uses a weighted average between these new values and the old values in the next iteration, continuing until a fixed point has been reached.

Accuracy. In this subection we assess the accuracy of our numerical solutions using two different methods. First, we check whether the statistics we are interested in are greatly changed when we use higher-order polynomials, more quadrature points or a wider range of grid points. Second, we assess the quality of the approximation given by the Chebyshev polynomials at points not on the grid. Here we report results only for the PCA case, as results are similar for CCA.

Table A.1 indicates the properties of the different numerical solutions that we check. In the first column are characteristics of the baseline solution that uses tensor product second-order Chebyshev polynomials. Solution I differs from the baseline by doubling the number of quadrature points, while Solution II extends the grid by including all points that occur in a random draw of 100,000 observations. Finally, Solution III uses tensor product third-order polynomials. Summary statistics for different versions of the algorithm are shown in Table A.2. The variations in the reported statistics are far too slight to be of any consequence for the analysis. Note that the creation and destruction volatilities are the most sensitive statistics, the reason being that these variables may be close to zero and we take logarithms of them.

Table A.3 assesses accuracy off the grid by reporting the average absolute percentage error and the maximum absolute percentage error for the four conditional expectations using a random realization of 100,000 observations. The weakest performance is observed for the expected value of the future benefits of the unmatched firm. In Figures A.1 through A.4, the four conditional expectations and their approximations are plotted for a particular random realization. The actual conditional expectations are calculated using a numerical procedure and thus are subject to a numerical error as well, although the error is very small. The figures document that approximation errors are basically unnoticable relative to the movements in the conditional expectation.

7.2. Data Sources. *Tables 2, 3A and Figure 3.* Series are seasonally adjusted, quarterly, taken from CITIBASE.

Q - Real gross domestic product (GDPQ), divided by over age 16 population, including resident armed forces, middle month (PO16).

C - Real consumption of nondurables (GCNQ) plus real consumption of services (GCSQ) plus real government consumption expenditures and gross investment (GGEQ), all divided by PO16.

I - Real Expenditures on durable consumption (GCDQ) plus real investment (GIFQ), all divided by PO16.

N - Civilian labor force, total employment, monthly (LHEM), converted to quarterly by simple averaging, divided by PO16.

Tables 3B, 4. Series are quarterly, seasonally adjusted by regressing the log of each series on seasonal dummies.

cre - Job creation rate for both startups and new establishments (POS), from Davis, Haltiwanger and Schuh, "Job Creation and Destruction" database.

des - Job destruction rate for both shutdowns and new establishments (NEG), from "Job Creation and Destruction" database.

N - Employees on nonagricultural payroll, manufacturing, monthly (LPM6), from CITIBASE, transformed into quarterly series starting at the middle month of each quarter, divided by PO16.

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			PCA	CCA
α	0.36	π	0.50	0.50
δ	0.025	ρ^x	0.068	0.068
γ	-1.00	l	1.27	1.27
β	0.99	b	2.220	2.077
ξ	0.95	c	0.203	0.196
σ_ϵ	0.007	σ_a	0.101	0.098

Table 1. Parameter Values.

	U.S. Data	PCA	CCA
ρ^n	0.032	0.0337	0.0292
λ^f	0.71	0.700	0.694
λ^w	0.45	0.452	0.458
σ_N/σ_Q	0.63	0.626	0.617

Table 2. Data Match for Parameter Selection.

	U.S. Data	PCA	CCA
A			
σ_Q	1.93 (0.0024)	1.45	1.63
σ_C/σ_Q	0.44 (0.16)	0.55	0.53
σ_I/σ_Q	3.06 (0.057)	2.71	2.85
$\sigma_{Q/N}/\sigma_Q$	0.42 (0.30)	0.40	0.39
B			
σ_{cre}/σ_N	4.71 (0.025)	7.48	8.01
σ_{des}/σ_N	6.86 (0.012)	6.17	5.90

Table 3. Comparison of U.S. and Model Data.

U.S. data are 1972:2-88:4. All series are logged and HP filtered.

		-3	-2	-1	0	1	2	3
	U.S. Data	0.27	0.15	0.04	-0.19	-0.58	-0.68	-0.60
Cov$[cre_{t+k}, N_t]$	PCA	0.17	0.13	0.06	-0.14	-0.70	-0.68	-0.52
	CCA	0.19	0.18	0.13	-0.04	-0.64	-0.63	-0.48
	U.S. Data	-0.63	-0.65	-0.59	-0.35	-0.01	0.29	0.45
Cov$[des_{t+k}, N_t]$	PCA	-0.35	-0.53	-0.72	-0.78	-0.24	-0.02	0.08
	CCA	-0.34	-0.57	-0.69	-0.73	-0.18	0.03	0.11
	U.S. Data	-0.39	-0.44	-0.47	-0.43	-0.14	0.18	0.34
Cov$[cre_{t+k}, des_t]$	PCA	-0.13	-0.14	-0.22	-0.47	0.43	0.57	0.48
	CCA	-0.12	-0.13	-0.23	-0.57	0.35	0.49	0.42

Table 4. Dynamic Correlations of Job Flows.

U.S. data are 1972:2-88:4. All series are logged and HP filtered.

	PCA	CCA	RBC	Hansen
Impulse Magnification	1.34	1.63	1.45	1.85
σ_Q/σ_z - Unfiltered	2.45	2.85	1.55	1.86
σ_Q/σ_z - HP Filtered	1.70	1.91	1.46	1.87

Table 5. Impulse and Total Magnification.

	Baseline	Solution I	Solution II	Solution III
Order of Polynomial	2	2	2	3
Coefficients per Polynomial	27	27	27	64
Hermite Quadrature Nodes	5	10	5	5
Simpson Quadrature Nodes	15	31	15	15
Range of K_t	$[20, 32]$	$[20, 32]$	$[20, 37]$	$[20, 32]$
Range of N_t	$[0.7, 1]$	$[0.7, 1]$	$[0.65, 1]$	$[0.7, 1]$
Range of $\ln z_t$	$[-3\sigma_z, 3\sigma_z]$	$[-3\sigma_z, 3\sigma_z]$	$[-5\sigma_z, 5\sigma_z]$	$[-3\sigma_z, 3\sigma_z]$

Table A.1. Properties of Different Numerical Solutions.

	Baseline	Solution I	Solution II	Solution III
ρ^n	0.0337	0.0337	0.334	0.0337
λ^w	0.452	0.452	0.452	0.452
σ_Q	0.145	0.145	0.144	0.145
σ_C/σ_Q	0.550	0.550	0.542	0.543
σ_I/σ_Q	2.71	2.71	2.72	2.74
σ_N/σ_Q	0.626	0.626	0.619	0.627
σ_{cre}/σ_N	6.17	6.17	6.35	6.11
σ_{des}/σ_N	7.48	7.48	7.54	7.50
$\text{Cov}[cre_t, N_t]$	−0.14	−0.14	−0.16	−0.13
$\text{Cov}[des_t, N_t]$	−0.78	−0.78	−0.78	−0.78
$\text{Cov}[cre_t, des_t]$	−0.47	−0.47	−0.44	−0.48

Table A.2. Sensitivity of Summary Statistics

Conditional Expectation in:	Average Absolute % Error	Maximum Absolute % Error
Equation (11)	0.00078	0.0164
Equation (12)	0.00051	0.0100
Equation (13)	0.00427	0.0874
Equation (15)	0.18818	5.0758

Table A.3. Accuracy Off the Grid.

This table reports indicated absolute errors using a random realization of 100,000 observations.

Figure 1. Impulse Responses of Job Creation and Destruction.

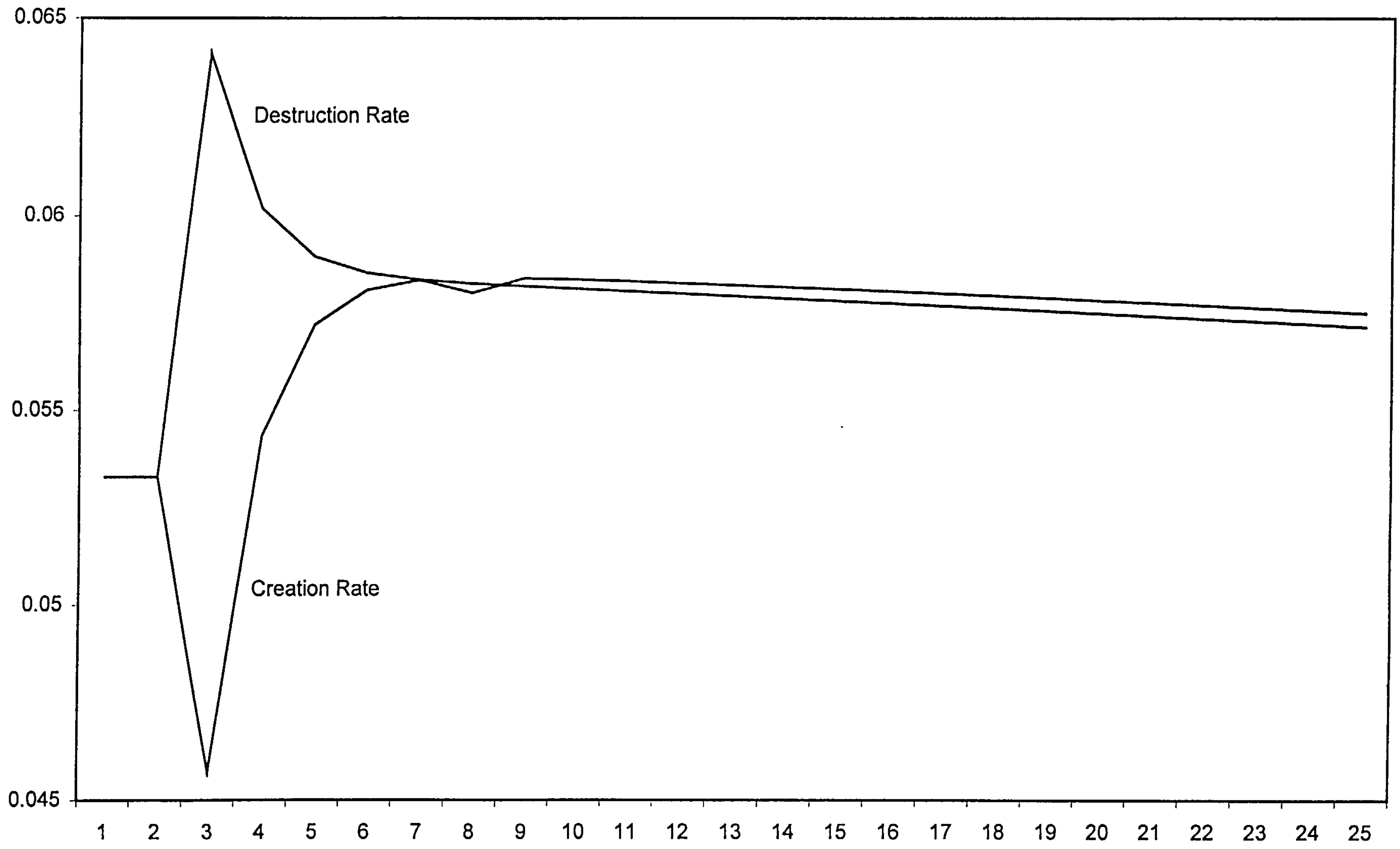

Figure 2. Impulse Responses of Productivity and Output.

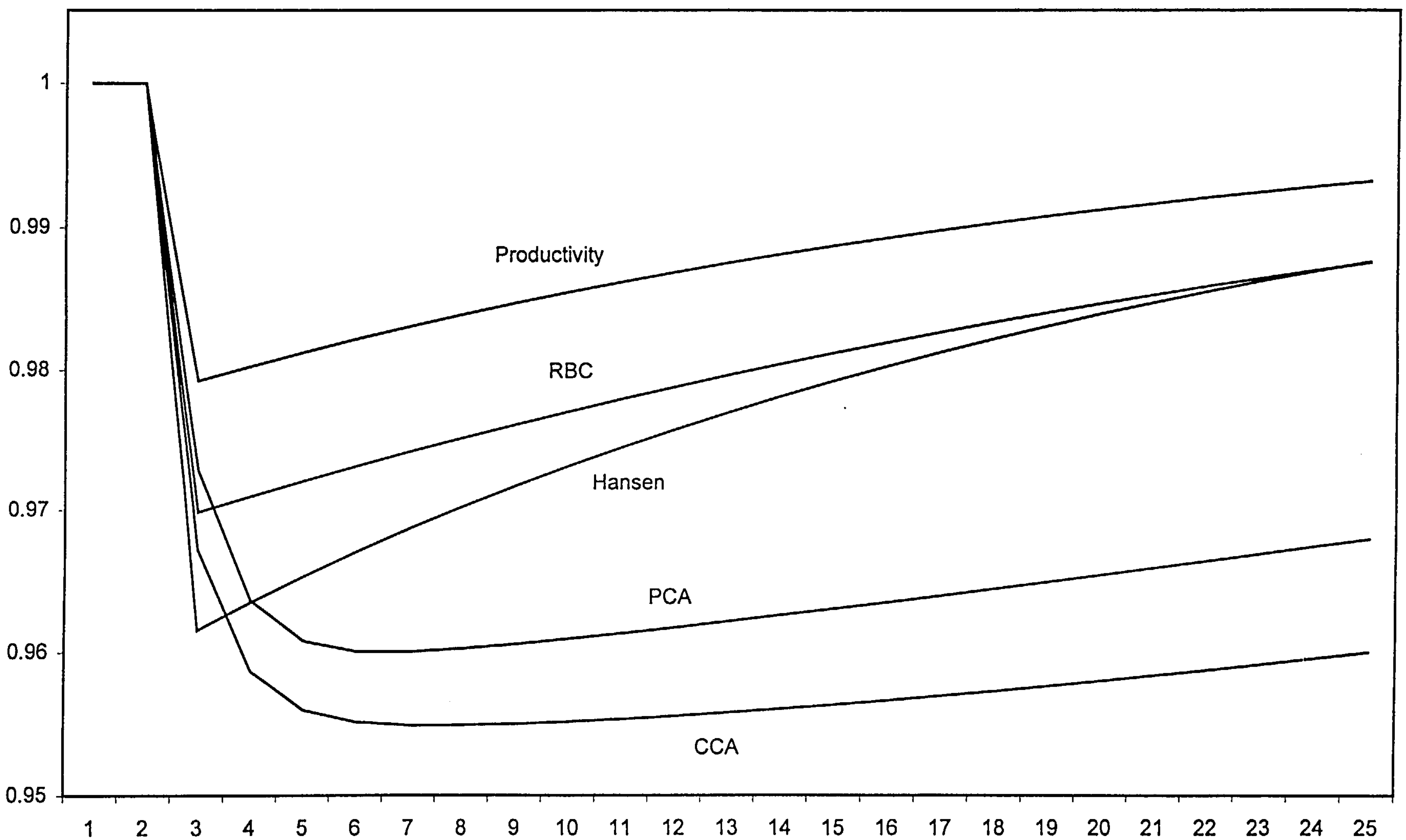

Figure 3. Autocorrelations of Output Growth Rates.

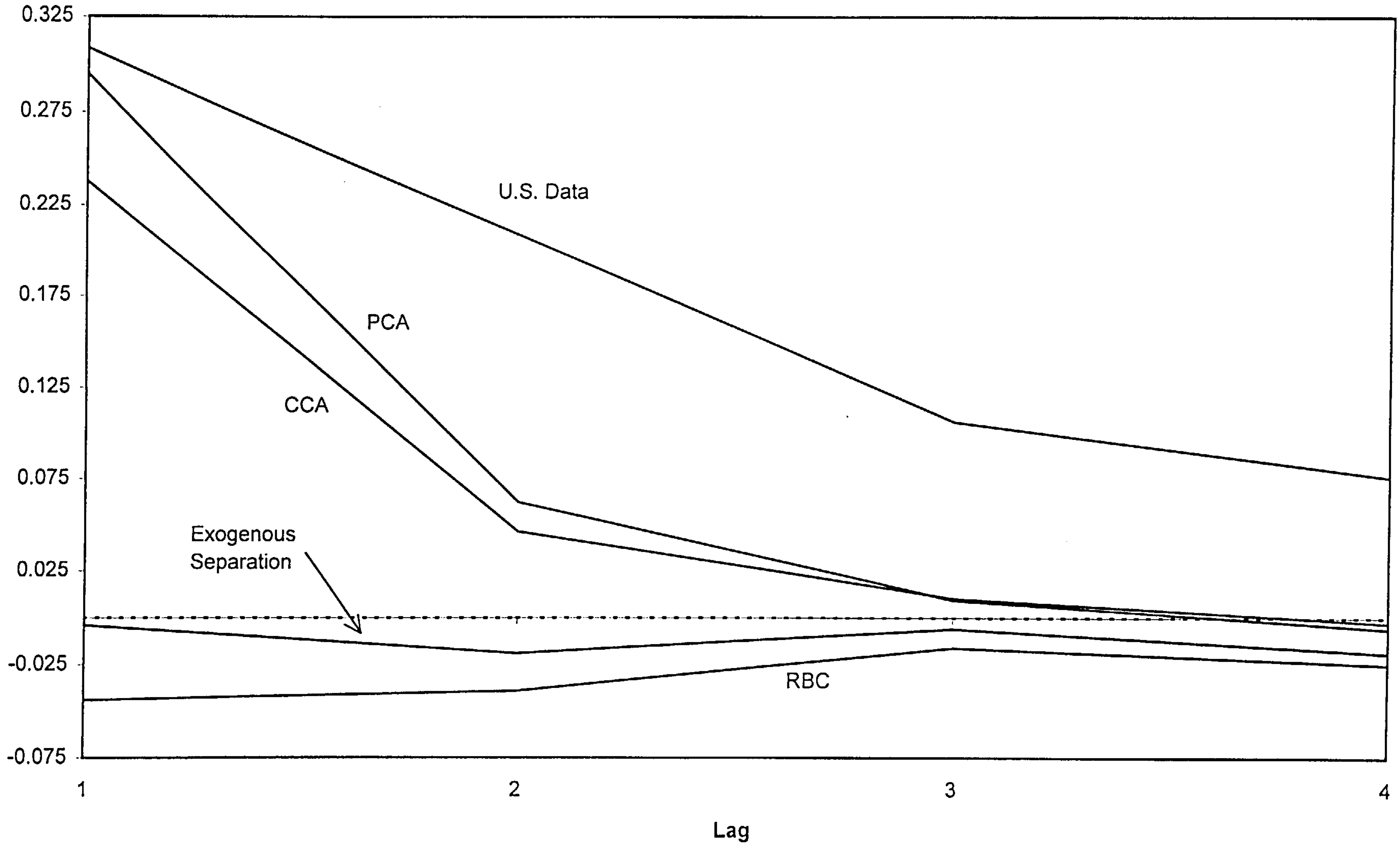

Figure 4. Impulse Responses under Endogeous and Exogenous Separation Rates.

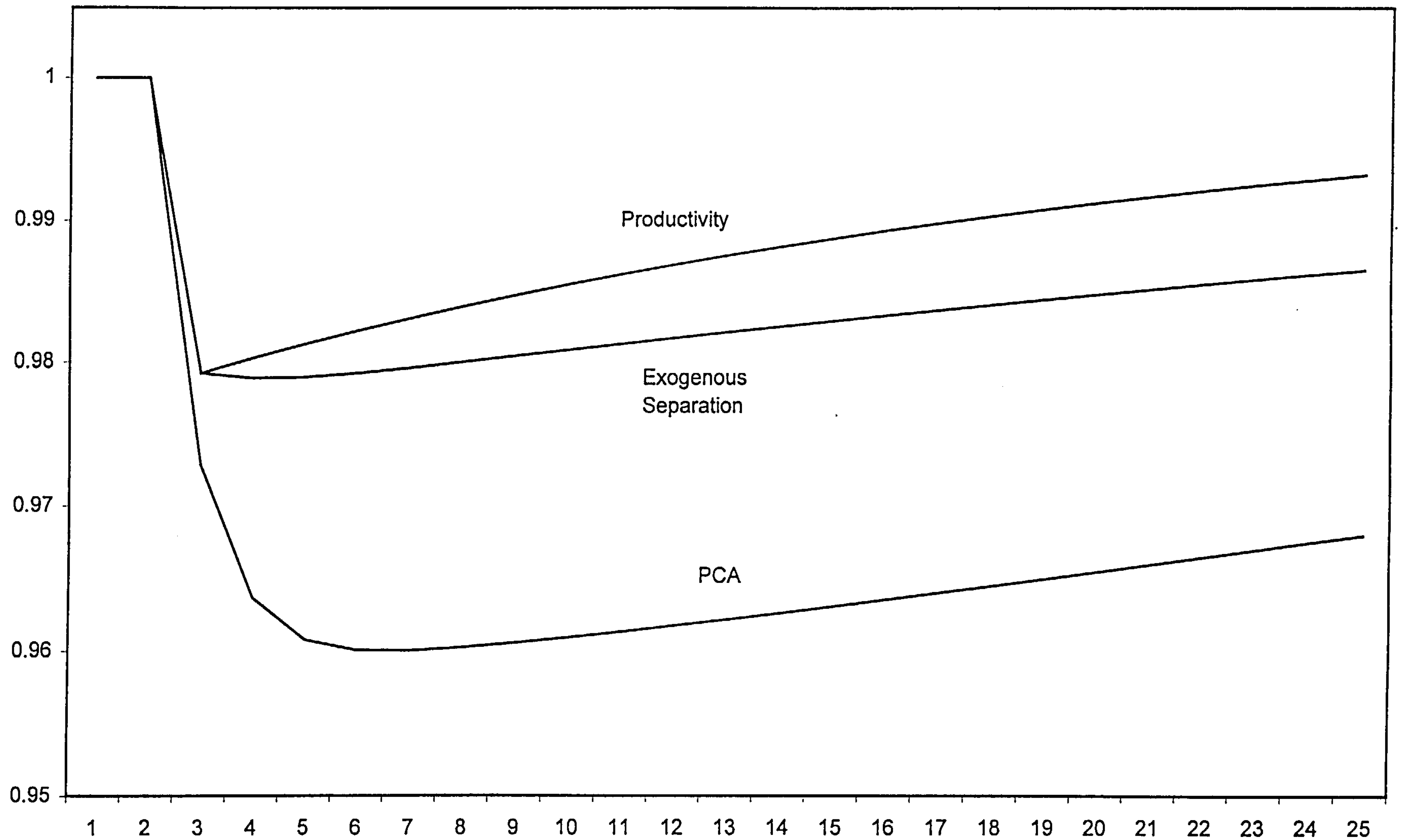

Figure 5. Impulse Responses of Capital.

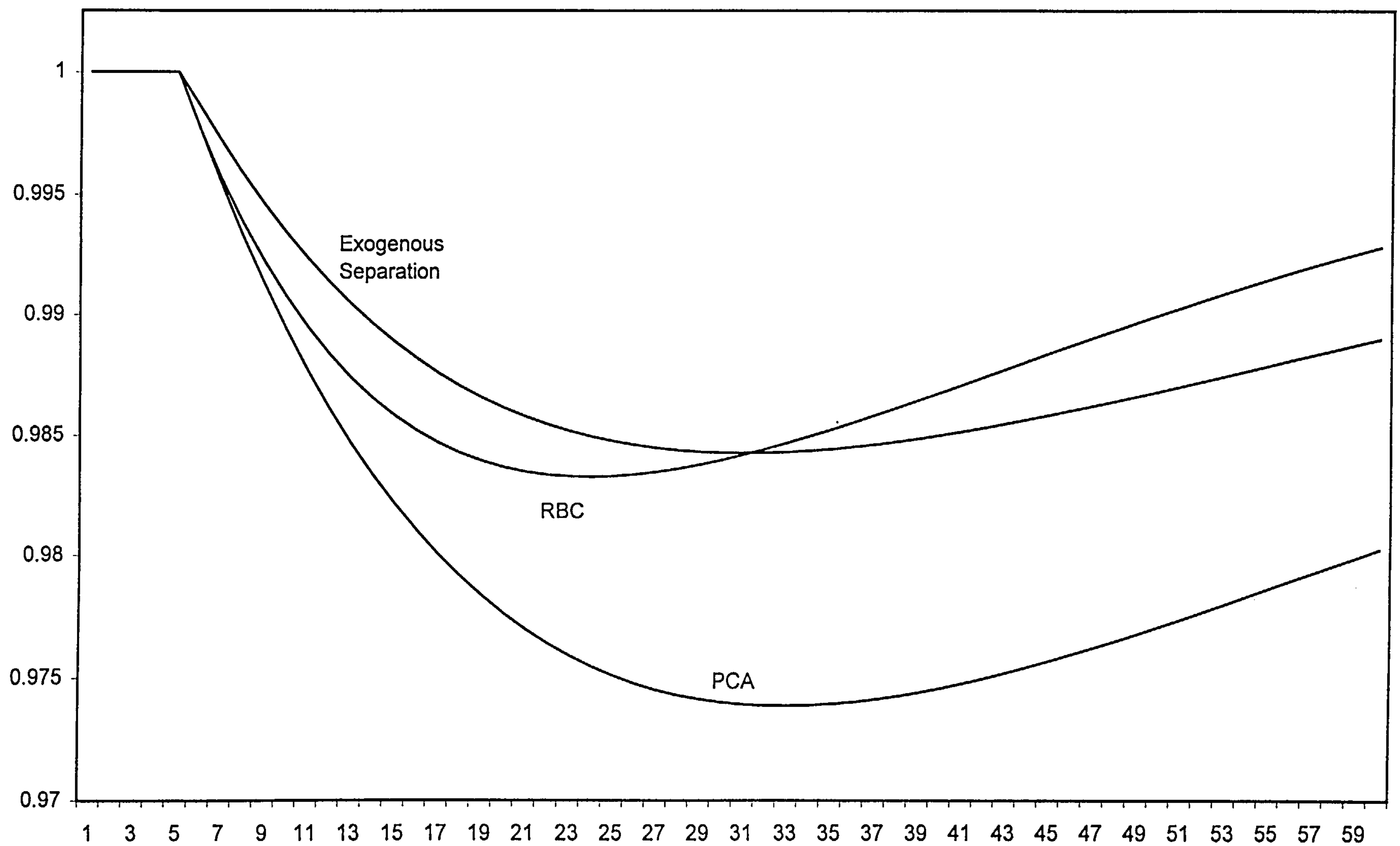

Figure 6. Effect of Capital Adjustment on Output and Rental Rates.

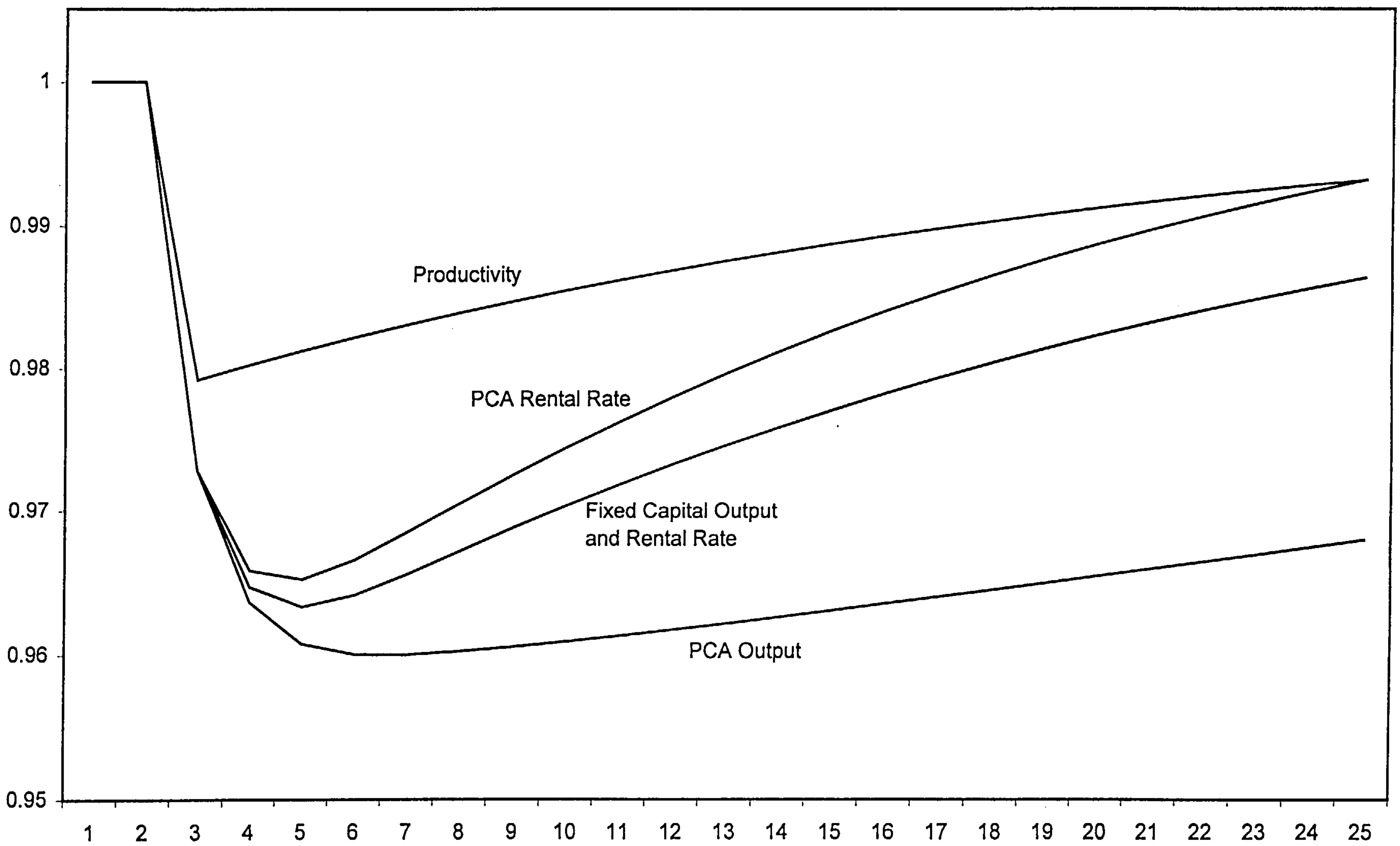

Figure 7. Effect of Fixed Capital on Endogenous Separation Rates.