Aggregative Disequilibrium Econometric Models of the Labour Market with Macroeconomic Shocks and Discouraged Workers

by

Vassilis A. Hajivassiliou
Department of Economics
London School of Economics

Revised February 2019

Abstract

In this paper, I first show how aggregation over submarkets that exhibit varying degrees of disequilibrium can provide a foundation to the classic "short-side" disequilibrium econometric model of Fair and Jaffee [12]. I then introduce explicit randomness in the aggregative model as arising from economy-wide demand and supply shocks, which are allowed to be serially correlated. The model makes explicit allowance for the discouraged worker phenomenon, whereby labour supply endogenizes the probability of excess supply prevailing in the market.

I apply suitable simulation estimation methods to circumvent hitherto intractable computational problems resulting from serial correlation in the unobservables in disequilibrium analysis. I show that the introduction of macroeconomic shocks has fundamentally different implications compared to the traditional approach that arbitrarily appends an additive disturbance term to the basic equation of the model.

The aggregative disequilibrium model with macroeconomic shocks and the discouraged worker effect is estimated from a set of quarterly observations on the labour market in US manufacturing. A major finding is that the introduction of macroeconomic shocks is able to explain a large part of the residual serial correlation that was plaguing traditional studies. Moreover, the new modelling technique yields considerably more satisfactory estimates

of the supply side of the markets.

Laroque and Salanié papers: add references

Add idea of Eaton and Quandt. My related ideas and aggregation

E-mail: vassilis@econ.lse.ac.uk
Address: Department of Economics
London School of Economics
Houghton Street
London WC2A 2AE

Keywords: Disequilibrium, Aggregation, Simulation Estimation Methods, Dynamic Limited Dependent Variable Models, Labor Markets, Discouraged Worker Effect

JEL Classification: 210, 820

Aggregative Disequilibrium Econometric Models of the Labour Market with Macroeconomic Shocks and Discouraged Workers

1 Introduction

Aggregation over submarkets that exhibit varying degrees of disequilibrium has a long tradition in economics. Since the pioneering work of Malinvaud [27] and Muellbauer [30], several authors have offered variations on the same theme. See, *inter alia*, Lambert [22], Kooiman [20], Andrews and Nickell [4], Hajivassiliou [18], and Quandt [35]. The basic aggregation approach has been proposed as providing a more disaggregated foundation to the classic "short-side" disequilibrium model of Fair and Jaffee [12]. See also Goldfeld and Quandt [13], Rosen and Quandt [40], and Quandt [34]. Moreover, estimation of a version of the aggregative model (Hajivassiliou [18]) only requires non-linear least squares with correction for conditional heteroskedasticity, thus circumventing some of the more severe computational problems of the ML estimation of the classic model.

In this paper, I introduce explicit randomness in the deterministic aggregation model as arising from economy-wide demand and supply shocks. I then show that this has fundamentally different implications compared to the traditional approach that arbitrarily appends an additive disturbance term to the basic equation of the model. The second innovation in this paper is to introduce simulation estimation methods, pioneered by McFadden [29], Pakes and Pollard [32], Laroque and Salanié [23], and Laroque and Salanié [24],to allow for serial correlation in the economy-wide demand and supply shocks. Such modelling is not feasible by traditional estimation methods because the non-linearity of the model would lead to intractable integrals.

The aggregative disequilibrium model with macroeconomic shocks is then estimated from a data set consisting of quarterly observations on the labour market in US manufacturing. A major finding is that the introduction of macroeconomic shocks is able to explain a large part of the hitherto unexplainable residual serial correlation that was plaguing traditional studies. Moreover, the new modelling technique yields considerably more satisfactory estimates of the supply side of the markets.

In Section 2 I present the aggregative disequilibrium model with macroeconomic shocks and contrast it to previous approaches. A maximum likelihood estimation procedure is proposed and analyzed. Technical details are given in Appendix A. Section 3 shows how to make explicit allowance for the "discouraged worker phenomenon," whereby labour supply endogenizes the probability of excess supply prevailing in the market. Section 4 presents the simulation estimation method that allows me to introduce serially correlated macroeconomic shocks in the aggregative disequilibrium model. The consistency and asymptotic normality of the simulation estimation method is also discussed in that Section. Section 5 describes the specifications of the sectoral demand and supply functions used in the empirical implementations. The quarterly data set used in this study is described in Section 6 and Data Appendix B. Section 7 discusses some preliminary issues in econometric implementation of aggregative disequilibrium models. Section 8 presents the empirical results. Concluding remarks are given in Section 9.

2 Macroeconomic Shocks and Aggregation

Think of the economy or the relevant market as consisting of J sectors assumed of equal size for simplicity; otherwise simple scale factors are needed. In sector j, $j = 1, \cdots, J$, notional demand and supply are denoted by D_t^j and S_t^j respectively, and, by the "short-side" rule of voluntary exchange (see Barro and Grossman [5]), transacted quantity is given by $Q_t^j = \min(D_t^j, S_t^j)$. Hence,

$$D_t^j = \bar{D}_t + \epsilon_t^j \tag{1}$$

$$S_t^j = \bar{S}_t + u_t^j \tag{2}$$

$$Q_t^j = \min(D_t^j, S_t^j), \tag{3}$$

where $\bar{D}_t (= X_t^d \beta^d + \eta_t \equiv D_t^* + \eta_t)$ and $\bar{S}_t (= X_t^s \beta^s + \theta_t \equiv S_t^* + \theta_t)$ are to be thought of as mean (economy-wide) demands and supplies, and ϵ^j, u^j are sector-specific demand and supply shocks. η_t and θ_t are unobservable economy-wide shocks. Dropping the time subscript for simplicity, I aggregate over sectors on the basis of a postulated distribution function of the shocks $F(\epsilon, u|\eta, \theta)$, conditioning on the temporal (economy-wide) randomness included in $\bar{D}_t$ and $\bar{S}_t$ in the form of η_t and θ_t. Note the lack of a j index, implying that the sector-specific shocks are drawn from an identical distribution, the drawings assumed independent across j.[1] As Muellbauer [30] shows, given condition (3), transacted quantity in the aggregate, conditional on the macro economic shocks η_t and θ_t, is given by

$$(Q|\eta, \theta) = \sum_{j \in \{D^j < S^j\}} D^j + \sum_{j \in \{D^j > S^j\}} S^j. \tag{4}$$

Let A be the set of sectors that are in excess demand, i.e., $\{j | D^j > S^j\} \equiv A$ and let B be its complement $\{j | D^j < S^j\} \equiv B$. Making the assumption of many markets so as to give an approximately continuous distribution $F(\cdot, \cdot|\eta, \theta)$, we can replace summations by integrals to obtain

$$\begin{aligned}
(Q|\eta, \theta) &= \int_B D^j dF(\epsilon, u|\eta, \theta) + \int_A S^j dF(\epsilon, u|\eta, \theta) \\
&= \int_B (\bar{D} + \epsilon^j) dF(\epsilon, u|\eta, \theta) + \int_A (\bar{S} + u^j) dF(\epsilon, u|\eta, \theta) \\
&= \int_B \bar{D} dF(\epsilon, u|\eta, \theta) + \int_A \bar{S} dF(\epsilon, u|\eta, \theta) + \int_B \epsilon \, dF(\epsilon, u|\eta, \theta) + \int_A u \, dF(\epsilon, u|\eta, \theta) \\
&= \bar{D} \int_B dF(\epsilon, u|\eta, \theta) + \bar{S} \int_A dF(\epsilon, u|\eta, \theta) + \bar{\epsilon} + \bar{u} \\
&= \bar{D} \cdot (1 - \pi) + \bar{S} \cdot \pi + \bar{\epsilon} + \bar{u},
\end{aligned} \tag{5}$$

[1] This independence of shocks across j might appear restrictive, given, for example the presence of macroeconomic shocks. Recall, however, that we are for the moment conditioning on such economy-wide shocks. Some of these shocks can be captured by the inclusion of economy-wide variables in D_t^* and S_t^*, e.g., money supply. Below, I investigate explicitly the effects of the randomness in the macroeconomic shocks η_t and θ_t.

where π is the proportion of the sectors that are in excess demand. The error term $\bar{\epsilon}$ denotes the average demand shock in the sectors that are in excess supply and $\bar{u}$ the average supply shock in sectors with excess demand. The proportion π is clearly dependent upon the magnitude of total excess demand $\bar{D} - \bar{S} \equiv (D^* - S^* + \eta - \theta)$ through the conditional density function $dF(\epsilon, u|\eta, \theta)$, and so are $\bar{\epsilon}$ and $\bar{u}$.

Hence, we see that under appropriate conditions, aggregating over micro-sectors in disequilibrium while conditioning on macroeconomic shocks predicts that transacted quantity will be given by the total mean demand and demand shocks weighted by the proportion of sectors in excess supply, plus the total mean supply and supply shocks weighted by the proportion of sectors in excess demand. In an exactly analogous manner, in the case of the switching approach on a single market, expected transacted quantity is given by the convex combination of expected demand and expected demand-error, given excess supply on one hand, and the expected supply plus the expected supply-error, given excess demand on the other. The weighting factor is in this case the probability of the single sector being in excess demand. Figure 1 summarizes the main result of this aggregation theory.

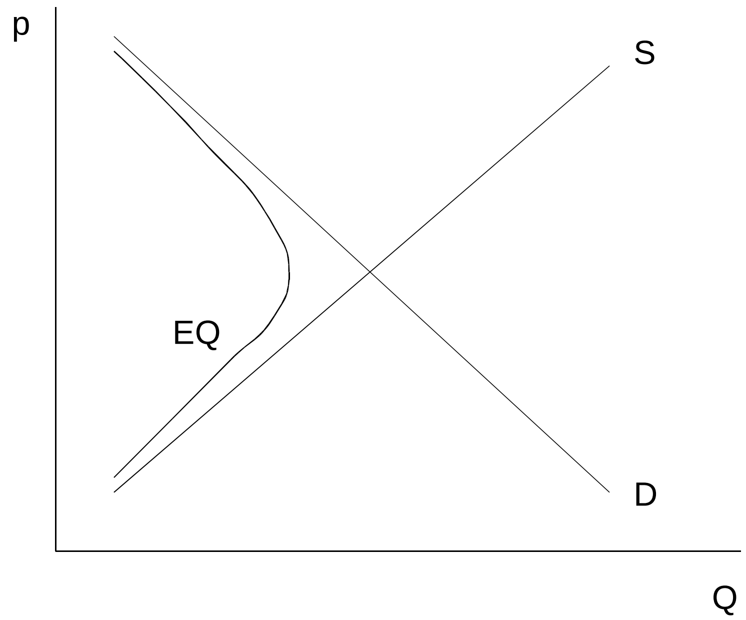

Figure 1

Now consider explicitly the implications of the presence of the macroeconomic shocks η and θ. Assume that η and θ are jointly normal with covariance matrix $\Omega_{\eta\theta}$ and *i.i.d.* across time. Also assume that the sectoral shocks ϵ and u are normally distributed and denote the excess demand variance by $\sigma^2 \equiv V(\epsilon - u)$. Such normality assumptions are customary in the literature. In summary,

$$\begin{pmatrix} \eta \\ \theta \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta\theta} \\ & \sigma_\theta^2 \end{bmatrix}\right), \quad \text{and} \begin{pmatrix} \epsilon \\ u \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} \sigma_\epsilon^2 & \sigma_{\epsilon u} \\ & \sigma_u^2 \end{bmatrix}\right). \tag{6}$$

Denote by $P(A)$ the probability of excess demand conditional on the macro shocks η and θ.

By the normality assumption, $P(A) = \Phi\left(\frac{D^*-S^*+\eta-\theta}{\sigma}\right)$ and equation (5) reads

$$(EQ\ |\eta,\theta) = D^* \cdot \left[1-\Phi\left(\frac{D^*-S^*+\eta-\theta}{\sigma}\right)\right] + S^* \cdot \Phi\left(\frac{D^*-S^*+\eta-\theta}{\sigma}\right) \tag{7}$$
$$-\sigma\ \phi\left(\frac{D^*-S^*+\eta-\theta}{\sigma}\right) + \eta - \Phi\left(\frac{D^*-S^*+\eta-\theta}{\sigma}\right)(\eta-\theta),$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the standard normal density and cumulative distribution functions respectively. This equation is derived from first principles in Appendix A. Denote the macroeconomic excess demand shock by $\zeta \equiv \eta - \theta$. This may be, for example, a function of unanticipated changes in the money supply.

To obtain the nonlinear regression function for the transacted quantity, Q_t, conditional on the explanatory variables, which I will use for estimation, I proceed as follows: By the properties of conditional expectations

$$E(Q) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} E(Q|\eta,\zeta)\ f(\eta,\zeta)\ d\eta\ d\zeta = \int_{-\infty}^{+\infty} E(Q|\zeta)\ f(\zeta)\ d\zeta, \tag{8}$$

where

$$E(Q|\zeta) = D^* \cdot \left(1-\Phi\left(\frac{D^*-S^*+\zeta}{\sigma}\right)\right) + S^* \cdot \Phi\left(\frac{D^*-S^*+\zeta}{\sigma}\right)$$
$$-\sigma \cdot \phi\left(\frac{D^*-S^*+\zeta}{\sigma}\right) - \zeta \cdot \Phi\left(\frac{D^*-S^*+\zeta}{\sigma}\right) + E(\eta|\zeta), \tag{9}$$

and $E(\eta|\zeta) = \beta_{\eta|\zeta} \cdot \zeta$, with $\beta_{\eta|\zeta} \equiv \sigma_{\eta\zeta}/\sigma_\zeta^2$.

Since $E_\zeta E(\eta|\zeta) = 0$, equation (8) becomes

$$E(Q_t) = \int_{-\infty}^{-\infty} \left[D_t^* \cdot (1-\Phi_t) + S_t^* \cdot \Phi_t - \sigma \cdot \phi_t - \zeta_t \cdot \Phi_t\right] \frac{1}{\sigma_\zeta}\phi\left(\frac{\zeta_t}{\sigma_\zeta}\right) d\zeta_t. \tag{10}$$

Note that $E_\zeta \zeta_t \cdot \Phi_t \neq 0$ and so σ_ζ is separately identified.[2] Very fast and accurate approximations for this integral exist in the form of Gaussian Hermite quadrature (see Butler and Moffit [8] and Hajivassiliou [15]). Assuming no serial dependence, the estimation criterion function to be minimized is then

$$F_{iid}(b) = \sum_{t=1}^{T} \left[Q_t - E(Q_t; b)\right]^2, \tag{11}$$

where $b = (\beta^{d\prime}, \beta^{s\prime}, \sigma_\zeta, \sigma)'$.

An important feature of this model is that *a priori* it should be able to accommodate at least some of the serial correlation that has plagued past disequilibrium studies. This can be seen by the presence of the term $\left\{\zeta_t \cdot \Phi\left(\frac{D_t^*-S_t^*+\eta_t-\theta_t}{\sigma}\right)\right\}$ that appears in equation (9). If this term was contaminating the errors of traditional models, then one could explain at least part of the serial correlation found in past studies that was exceedingly difficult to handle. This conjecture is confirmed by the empirical results below.

[2]Note, however, that σ_η^2 and σ_θ^2 are not separately identified.

3 Modelling the Discouraged Worker Effect

A well-documented phenomenon for markets with binding quantity constraints is that participants respond endogenously to the probability of a constraint binding. For example, in situations with significant liquidity constraints affecting consumer behaviour, an important finding (Grant 2002, Jappelli 1990 etc.) is that the more poorly educated people, households headed by women, and ethnic minorities housholds are *less* likely to hold debt and *less* likely to face binding liquidity constraints seems rather odd at first glance. In this section we offer an explanation of such findings by making the probability of encountering a binding liquidity constraint affect a household's notional demand for credit. This feature of our model allows explicitly that people who realize rationally that based on their characteristics they are very likely to face a binding constraint (e.g., uneducated people, and households headed by women or minorities), such people may feel discouraged from applying for credit in the first place. This "discouragement effect" on an individual's demand for credit implies a certain fixed point between the probability of a binding credit constraint entering Demand and the overal probability of S=min(D,S) (i.e., the prob of the credit constraint binding) taking place in the credit market at that time.

In greater detail:

$$D = X_d\beta_d + \gamma \times Prob(D > S) + \epsilon_d, \qquad S = X_s\delta_s + \epsilon_s$$

where

$$Prob(D > S) = Prob(\epsilon_s - \epsilon_d < X_d\beta_d - \gamma \times Prob(D > S) - X_s\delta_s$$

It should be noted that this modelling device is in the spirit of Eaton and Quandt [10].

4 Simulation Estimation Methods and Serially Correlated Macroeconomic Shocks

One would expect, *a priori*, that the macroeconomic shocks η and θ introduced in the previous section are serially correlated because such shocks typically incorporate the effects of government macroeconomic monetary and fiscal policy and the general real and nominal state of the economy. With classical econometric methods, however, allowing for this possibility leads to intractable computational problems. See, for example, Laroque and Salanié [24] and Richard [37] for a discussion of this issue.

To be more specific, recall equation (7), which describes the conditional expectation of the transacted quantity in the economy, Q, given the evolution of the macroeconomic shocks η and θ. Assuming that these errors are *i.i.d.* over time as in (6), I was able to show that the expected value of Q can be obtained by expression (10), which can be evaluated by numerical quadrature techniques. Assume now instead that the errors follow the bivariate stationary Gaussian AR(1) process:

$$\begin{aligned} \eta_t &= \rho_\eta \eta_{t-1} + \nu_t \qquad |\rho_\eta| < 1 \\ \theta_t &= \rho_\theta \theta_{t-1} + \mu_t \qquad |\rho_\theta| < 1 \end{aligned} \tag{12}$$

Given that the macro shocks appear non-linearly in the regression function (7), efficient classical estimation would require integration of order $T \approx 140$.

$$E(Q_1, \cdots, Q_T) =$$

$$\int_{-\infty}^{-\infty} \cdots \int_{-\infty}^{-\infty} E(Q_1, \cdots, Q_T | \eta_1, \zeta_1, \cdots, \eta_T, \zeta_T) \; f(\eta_1, \zeta_1, \cdots, \eta_T, \zeta_T) \; d\eta_1 \; d\zeta_1 \; \cdots \; d\eta_T \; d\zeta_T$$

$$= \int_{-\infty}^{-\infty} \cdots \int_{-\infty}^{-\infty} \prod_{t=1}^{T} \{E(Q_t | \eta_1, \zeta_1, \cdots, \eta_T, \zeta_T)\} \; f(\eta_1, \zeta_1, \cdots, \eta_T, \zeta_T) \; d\eta_1 \; d\zeta_1 \; \cdots \; d\eta_T \; d\zeta_T \quad (13)$$

Given that all $E(Q_t | \cdots)$ terms are interdependent because (η_t, θ_t) are serially correlated, this integral cannot be reduced to a product of univariate integrals.

To overcome this problem, one can use the following simulation estimation procedure:[3] Given a trial set of parameter values for β's, $\rho's$, σ's etc., and a set of initial conditions $\{\eta_0, \theta_0\}$, we draw R sequences of $\{\eta_t, \theta_t\}_{t=1}^{T}$ and calculate the implied R sequences for the endogenous variable Q of the system, say R sequences $\{\tilde{Q}_t^r(b)\}_{t=1}^{T}$, $r = 1, \cdots, R$. The empirical average $\frac{1}{R}\sum_{r=1}^{R} \tilde{Q}_t^r(b)$ will be an unbiased and consistent simulator for $EQ_t(b)$. The continuity of the function $E(Q|b, \eta, \theta)$ together with the mixing property of the macro shocks η and θ, implies that the distribution of Q will be mixing as well. Then, minimizing with respect to the parameters b the quadratic distance between Q and the average of $\tilde{Q}$ over simulations

$$F_{AR1}(b) = \sum_{t=1}^{T} \left[Q_t - \frac{1}{R} \sum_{r} \tilde{Q}_t^r(b) \right]^2, \tag{14}$$

defines a consistent and asymptotically normal estimator for the parameter vector b, provided R rises at least as fast as $\sqrt{T}$. This follows from results in Andrews [3] on empirical process theorems on serially dependent processes.[4] See also Laroque and Salanié [23] and Salanié [41] for the use of simulation estimation methods to facilitate the estimation of disequilibrium models.[5]

5 Data

In this paper, the market under examination is the aggregate labour market in the U.S. manufacturing sector and the period covered is 1948QI–1983QII. The data used are *seasonally unadjusted* quarterly series contained in the CITIBANK data base, compiled by the Council of Economic Advisers, or compiled by the Federal Reserve Board. Details are provided in Appendix B.

[3]Such a simulation estimation method was independently proposed and evaluated in a Monte Carlo study by Laroque and Salanié [24].

[4]An important caveat is that to my knowledge all asymptotic results for simulation estimators assume mixing processes. In practice, however, macroeconomic time series tend to be non-stationary. It is not clear whether or not the stationary results can be extended to the non-stationary case.

[5]Notice that the aggregation approach adopted here avoids a key difficulty of typical disequilibrium models and other limited dependent variable models, because the quantity I simulate is *continuously differentiable* in both the parameters and the errors that are being simulated. Other simulation estimation methods for disequilibrium models, e.g., Laroque and Salanié [23], are only piece-wise continuously differentiable. The number of simulations, R, I used below was 100.

6 Specification of Demand and Supply

6.1 Demand:

The most general specification I tried was the following (in logarithmic form):

$$D^*_t = a_0 + a'_1 \cdot \{\texttt{seasonal dummies}\} + a_2 \cdot \texttt{T} + a_3 \cdot \texttt{W}_t + a_4 \cdot \texttt{Y}_t + a_5 \cdot \texttt{W}_{t-1} + a_6 \cdot \texttt{Y}_{t-1} + a_7 \cdot \texttt{W}^*_t. \quad (15)$$

This corresponds to the marginal productivity condition of cost-minimization of the neoclassical firm. $\texttt{W}$ is the (gross) real wage. I tried both deflating by the CPI index and by the theoretically more relevant WPI deflator.

$\texttt{Y}$ is industrial production and $\texttt{T}$ is a time trend supposed to capture secular changes in the capital stock and other long term trends in technology. In a disequilibrium model, $\texttt{Y}$ is relevant as a quantity signal for a firm that is possibly rationed on the goods market, as it also is in an imperfect competition setting since it affects the marginal revenue product of labour. $\texttt{Y}_t$ is treated as predetermined — through exogenous government policy and autonomous aggregate demand shocks.[6]

$\texttt{W}_{t-1}$ and $\texttt{Y}_{t-1}$ were tried both for remedying some effects of serial correlation in the errors, and as possible persistence effects due to adjustment costs in employment decisions. $\texttt{W}^*_t$ is a measure of the wage expected (at t) to rule next period. (For a model that shows that the rational firm facing adjustment costs with respect to employment decisions will be both backward ($\texttt{W}_{t-1}$) and forward ($\texttt{W}^*_t$) looking, see Sargent [42].) $\texttt{W}^*_t$ was somewhat mechanically constructed by the ARMA Box-Jenkins [7] methodology.[7] The most satisfactory parsimonious ARMA specification appears to be an AR(2) with drift, a time trend and seasonals.[8] $\texttt{W}^*_t$ are the predictions from this fitted equation.

6.2 Supply:

Here the most general specification (again in logarithmic form) was:

$$S^*_t = \beta_0 + \beta'_1 \cdot \{\texttt{seasonal dummies}\} + \beta_2 \cdot \texttt{X}_t + \beta_3 \cdot \texttt{X}_{t-1} + \beta_4 \cdot \texttt{R}_t$$
$$+ \beta_5 \cdot \texttt{POTL}_t + \beta_6 \cdot \texttt{POTL}_{t-1} + \beta_7 \cdot \texttt{X}^*_t + \beta_8 \cdot \texttt{RELW}_t + \beta_9 \cdot \texttt{RELW}_{t-1}. \quad (16)$$

Such an equation may be obtained from the intertemporal maximization problem of a representative worker. $\texttt{X}_t$ is the after-tax (net) wage he/she receives deflated by the consumer price index. $\texttt{X}^*_t$ is the worker's expectation of the future net wage, constructed once more using the most parsimonious ARMA specification for $\texttt{X}_t$, in this case a random walk plus constant, a trend and seasonals. $\texttt{X}_{t-1}$ may be rigorously justified by habit-formation which makes the utility function intertemporally nonseparable.

$\texttt{R}_t$ is the ex ante real interest rate which plays an important role in the intertemporal labour substitution hypothesis; it affects the choice at the margin of working more now and

[6] A more appropriate approach would be to model explicitly spillovers between labour and goods markets.
[7] The exact forecasting equations used are available from the author upon request.
[8] Evidence on this issue is given also in Altonji [1] and in Altonji and Ashenfelter [2].

saving versus taking more leisure and borrowing or running down assets. The nominal interest rate variable used was the 3-month Treasury bill rate; this may be problematic, since Treasury bills were not readily accessible to the average worker over the study period. However, most studies on intertemporal consumer-worker optimization use this and/or similar variables (see e.g., Hansen and Singleton [19], Mankiw, Rotemberg, and Summers [28]) and the results appear to be quite robust to the choice of nominal-`R` variable.

$\mathtt{POTL}_t$ is a measure of the full potential man-hours that could be worked if all population of working age were attracted to the manufacturing labour force. Rosen and Quandt [40] and the subsequent studies mostly use as $\mathtt{POTL}_t$ the total civilian population of working age times the average man-hours worked in the economy, hence making the implicit assumption that if more people were attracted in the labour force, they would be working the same hours as those hitherto employed. This measure of `POTL`, however, creates a serious econometric problem: if average hours worked are constructed, as to be expected, by dividing the actual man-hours worked by the civilian labour force, I have directly introduced endogeneity on the RHS of the equation to be estimated for labour employment, in that a (non-linear) function of the dependent variable has been entered directly on the RHS. To avoid this problem, `POTL` is measured here by the total civilian labour force. $\mathtt{RELW}_t$ is entered as a measure of the wage of production workers in manufacturing, relative to the one of such workers in the overall labour market. This attempts to capture the relative attractiveness of seeking employment in the manufacturing sector, as opposed to the "average" market.[9]

7 Econometric Issues

Before discussing the empirical results, some general issues are noted. First, note that the initial Rosen and Quandt [40] study modelled the wage in an explicitly endogenous way by appending a wage-adjustment equation to the three basic equations of the switching model:

$$\ell n W_t - \ell n W_{t-1} = \gamma_1(\ell n L_t^D - \ell n L_t^S) + \gamma_2 V_t + \xi_t, \tag{17}$$

where for V_t, three alternatives were tried: (i) a vector of ones, (ii) the unionization rate and (iii) the change in the unionization rate. MLE was carried out on equations (1), (2), (3) and (17). In his latter study, Quandt [33] decided to drop equation (17) essentially for computational reasons. I chose Quandt's latter approach for better comparability with past studies.

The second issue is the treatment of *serial correlation*. It is a well known fact of economic life that aggregate data are strongly serially correlated. Robinson [38] suggests and Hajivassiliou [16] proves that serial correlation in the disequilibrium switching model with normally distributed errors does not pose consistency problems for MLE, so the hope in past

[9] Though the standard choice-at-the-goods-leisure-margin model predicts a role for unearned income (for fixing the intercept of the budget constraint), no such term was included. Instead of attempting the intractable task of modelling the lag structure from the life-cycle model that relates unearned income and hours of work, dropping unearned income from the model altogether seems to be a reasonable way to proceed.

studies was that it would not be too critical if serial correlation were not fully overcome.[10] Note that Gourieroux et al. [14] also derive general conditions for misspecified MLE to be consistent, so the result that disequilibrium MLE remains consistent in the presence of serial correlation of some forms could have been derived as a special case of their results. Using classical estimation methods, correct treatment of serial correlation in non-linear models in general and in disequilibrium models in particular is extremely intractable (see inter alia Quandt [33] and Lee [25]). Serial correlation of a restrictive form was introduced in the aggregative disequilibrium model of Hajivassiliou [18] in the following manageable way: allowing the error v_t corresponding to the economy-wide temporal random component to be autocorrelated, the appropriate estimation procedure is NLLS with an autoregressive error.[11]

There are two main novelties in this paper: First, through the introduction of macro shocks in the aggregative disequilibrium models, residual serial correlation is introduced explicitly as part of the theory. I am thus able to explain at least part of the severe residual serial correlation found in previous disequilibrium studies. Second, the simulation estimation method developed in Section 3 and in Laroque and Salanié [24] allows me to introduce explicit serial correlation in the form of (12).

A related issue that I address carefully here is the presence of *seasonality*. Given the non-linearities of the model, one should use seasonally unadjusted data and carry out de-seasonalization by the inclusion of dummy variables on both D and S sides, *simultaneously* with the estimation of the structural parameters of the model. Even though this is a computationally very demanding task, I pursue this approach here. To my knowledge, the problems with using de-seasonalized data are not acknowledged in most non-linear studies (see, for example, Hansen and Singleton [19]).

8 Empirical Results

Table 1 summarizes the four alternative estimated versions of equation (7) considered here, and Tables 2 and 3 present the results. See Appendix B for the exact definitions of variables. AGD refers to the aggregated disequilibrium model with the macroeconomic shocks η_t and θ_t assumed to be equal, an assumption frequently made in the past literature, estimated by NLLS with heteroskedasticity consistent covariance matrix. For this model, let $v_t \equiv \eta_t = \theta_t$.[12] AGDSC is the corresponding model that allows for the error term v_t to follow an $AR(1)$ process. AGDM is the model (7) with i.i.d. macroeconomic shocks (6) allowed explicitly and not forced to be equal. Finally, AGDMSC denotes the aggregative model with macro shocks following the bivariate AR(1) given by (12).

The signs of the coefficients come out as predicted by theory and as also reported by similar studies (see, e.g., Rosen and Quandt [40], Romer [39], Quandt and Rosen [36], and Quandt [33]). The wage effect is unambiguously negative on the demand. Magnitudes of the coefficients cannot be compared to the ones of the aforementioned studies as they use data

[10] Validity of inferences would be affected though, as the standard errors would be inconsistent. On this issue, see Newey and West [31].

[11] For other attempts to allow for (restrictive) types of serial correlation in disequilibrium models, see Laffont and Monfort [21] and Quandt [33].

[12] This model is studied in Hajivassiliou [18]. See also Muellbauer [30].

Table 1: Summary of Estimated Models

AGD	$EQ_t = D_t^*[1-\Phi_t] + S_t^*\Phi_t - \sigma\phi_t + v_t$	v_t i.i.d.
AGDSC	$EQ_t = D_t^*[1-\Phi_t] + S_t^*\Phi_t - \sigma\phi_t + v_t$	v_t AR(1)
AGDM	$EQ_t = E_\zeta\left\{D_t^*[1-\Phi_t] + S_t^*\Phi_t - \sigma\phi_t - \Phi_t\zeta\right\}$	v_t, ζ_t i.i.d.
AGDMSC	$EQ_t = E_\zeta\left\{D_t^*[1-\Phi_t] + S_t^*\Phi_t - \sigma\phi_t - \Phi_t\zeta\right\}$	v_t, ζ_t bivariate AR(1)

of different periodicity. However, the positive effect of real industrial production on labour demand is strongly confirmed (asymptotic t statistics greater than 5). In general, a positive elasticity of supply with respect to the (after tax) wage is found. In some estimations, the contemporaneous after tax wage comes out negative, but statistically insignificant. While this agrees with the studies cited above, and while economic theory leaves this elasticity unsigned, it is interesting to note that the generally positive sign of the one-period lag of this variable suggests the existence of adjustment lags. Changes in the potential labour force have a positive contemporaneous effect on the labour supply (though not of such pervasive significance: t rarely exceeds 2). The lagged effects of the potential labour force are not well determined in general. As predicted by theory, the relative wage in the manufacturing sector compared to the overall economy one, affects strongly in a positive way the supply of labour to the manufacturing sector. The σ_{ED} parameter, which is the standard deviation of excess demand standardizing the probability expressions, comes out positive as it should.

Trend variables supposed to capture capital stock movements and long-term productivity-technology changes in labour demand, and changes in participation rates in labour supply, are also tried. These have coefficients generally of the wrong sign (positive on demand) and rarely very robust to specification changes. The same applies to quarterly dummy variables that model for seasonality. This instability may simply point out the already noted computational problems, of dealing with seasonality in such non-linear models. Seasonality was found statistically strongly significant in all four models estimated, with LR statistics in excess of 40, against a $\chi^2_{1\%}(6) = 16.8$.

The sign of the real interest rate effect comes out positive as the intertemporal labour substitution hypothesis predicts, and is in general statistically very highly significant.[13] To test the "no fiscal illusion" hypothesis, the (log of the) real wage and the (log of the) (`1-TH`) variable were entered separately with different coefficients. Under the "no fiscal illusion" hypothesis, the equality of these two coefficients should not be rejected, which indeed is the case (with χ^2's in all cases less than 1.5).

I further attempted to examine the significance of the appropriate measures of expected wage on the labour demand and supply. I was unable to carry out such tests because of very strong collinearity between current and lagged wages, and the expected measures. It seems unlikely that these collinearities would have been reduced by refinements of the forecasting equations.

The estimates in Table 2 labelled AGDSC were obtained by allowing the error v_t in the aggregative disequilibrium model (with equal macro shocks) to follow a (stationary) au-

[13] Estimates were also obtained in Hajivassiliou ([18]) by the MLE switching-regimes disequilibrium approach (Fair and Jaffee [12] and Maddala and Nelson [26]). The closeness of the MLE results to those from the aggregative models (AGDM and AGDMSC) provides the basic support for the aggregation approaches.

toregressive process of order 1. The very high value of ρ (0.87) and its strong statistical significance cast doubt on the reported estimated standard errors, while not on the consistency of the parameter estimates. This is an area where the AGDM is vastly superior to the AGD model. There is only weak evidence of any residual serial correlation,[14] which seems to imply that the previous findings were directly caused by omission of macroeconomic shocks from the models. Furthermore, the introduction of the macroshocks improves substantially the fit of the aggregation model — see the correlations between the dependent variable LE (labor employment) and fitted $\widehat{LE}$ in Tables 2 and 3.

I finally report several specification tests of the aggregative disequilibrium models. Since the standard deviation parameter σ appears both in the cumulative normal terms (probability of excess D in the major functional form of equation (7)), as well as in the conditional expectations (normal density) term, a potentially powerful test of specification is to let the two σ's differ, say σ_1 inside the *c.d.f.* and σ_2 inside the correction term, and test whether or not they differ significantly. Neither test rejects the specification in this sense (the largest "LR" comes out at 1.366 for AGD against a $\chi^2_{10\%}(1) = 2.71$).[15] Furthermore, Table 3 reports some wage-exogeneity tests that employ the methodology in Hajivassiliou [17]. These tests, which are based on the Lagrange Multiplier principle, amount to obtaining OLS estimates of the reduced-form (RF) equations of the variables suspected for endogeneity, and testing the significance of these RF residuals when entered as additional variables on the D and S sides.[16] Some of the results reject marginally the exogeneity of real wage with the highest LR statistic being 14.8 against a critical value of $\chi^2(4) = 13.3$ at the 1% level of significance, whereas others do not. For example, AGDMSC does not reject the exogeneity of the nominal wage with a $LR = 2.18$, vs. a critical value of $\chi^2_{10\%}(2) = 4.6$. I hence view the evidence on this matter as mixed.

[14] See the results of model AGDMSC and those given in Table 3 below.

[15] "LR" is not exactly the usual likelihood ratio test, given that estimation of equation (5) is by NLLS. It is a valid measure of "distance", however, and also distributed asymptotically as $\chi^2(d.f.)$ Moreover, there is evidence that it possesses high power, particularly when used as a specification test.

[16] For rigorous definitions of various types of econometric exogeneity, see Engle et al [11].

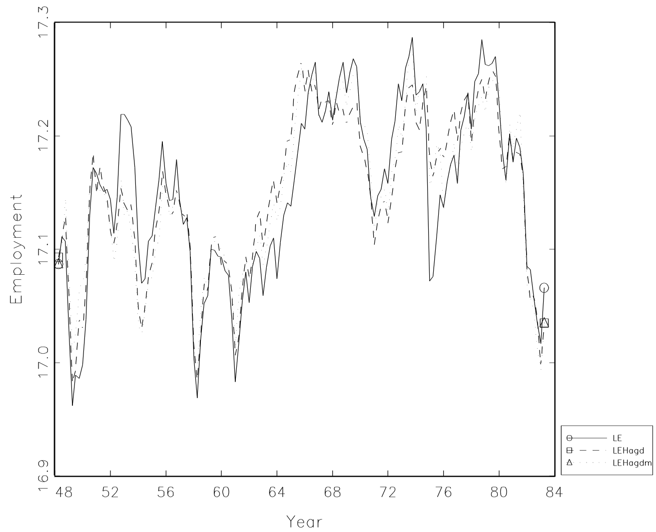

Figure 2

To further evaluate the estimation results, I present two measures of fit between actual data and predictions of the model. First, employment predictions, using the "preferred" version AGDMSC, track employment very well. See the very high correlation figures between predicted and actual employment appearing in Table 2. The model is able to reproduce quite accurately even turning points in the LE series — the simple correlation between the actual LE series and the one predicted by the estimated equation (7) is over 0.9. Figure 2 presents actual LE together with LE predicted by the AGD and AGDM models. Their good tracking ability should be obvious, especially the one of AGDM. Of course, since LE is likely to be non-stationary, it is quite easy even for unsatisfactory models to be able to predict well its *level*. I therefore performed other tests of goodness-of-fit in *first-differenced* form. In one such test, the estimated models were asked to predict the probability of excess demand at each time period (or the proportion of sectors in excess demand in our preferred interpretation) and then these predicted probabilities were examined for conformity to some well defined measure of "tightness" in the economy. To construct such a measure I first defined

`XDY` ≡ `(real GNP -- potential real GNP)/potential real GNP`,

where potential real GNP is a series obtained from the Council of Economic Advisors (CEA). A second measure of slackness I tried was the level of unemployment (`U`).[17]

All the predicted probabilities correlate very highly among themselves, and quite satisfactorily with both the `XDY` measure and the unemployment rate (`-U`). I present (annualized) values of `PROBH` predicted from the model formulated *in first differences*, and changes in `XDY01` (the latter measure is simply changes in `XDY` transformed to lie between 0 and 1). The ability of the predicted probabilities series to track turning points

[17]Unfortunately this series is seasonally adjusted.

in the *changes* in the tightness-of-the-economy measure is quite impressive. See Figure 3.

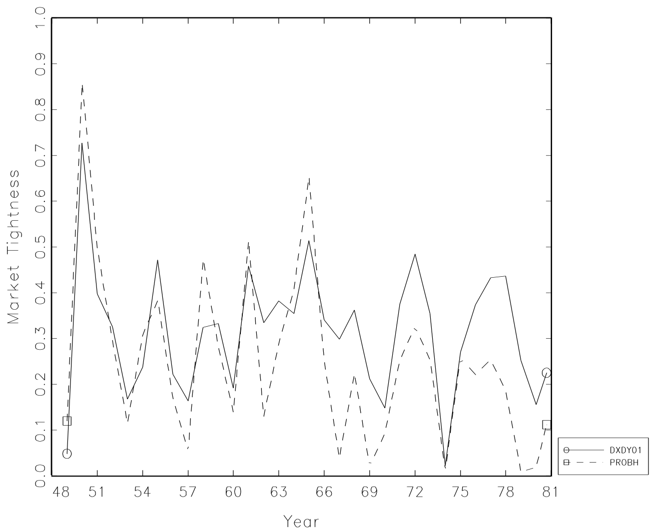

Figure 3

9 Conclusion

A simple aggregated-over-micro-disequilibria model with explicit macroeconomic shocks was formulated and tested with favourable results. This model predicted that (apart from a correction term and a random error) aggregate employment in the market in question would be given by a convex combination of demand and supply, the weighting factor being the proportion of sectors that are in excess supply. The estimates were close to ones I obtained from the standard disequilibrium switching model, thus justifying the close relation between the two models that I stressed in this paper. The major advantage of the new model is its ability to eliminate most of the very strong residual serial correlation exhibited in past aggregative disequilibrium studies.

The second innovation of this paper was the development of a simulation estimator for aggregative disequilibrium models, which allowed the explicit allowance for serially correlated errors as part of the theoretical setup, as opposed to residual serial correlation. Estimation of such models using classical methods is computationally infeasible.

The signs of estimated coefficients are, in general, as predicted by theory — significantly negative effects of wage on demand and of a linear trend (technology, etc.) on supply, significantly positive elasticities of demand with respect to real output and of supply with respect to potential labour force and the real interest rate. A measure of expected change in wage was found to introduce strong collinearity, thus preventing reliable tests of standard predictions of the intertemporal labour substitution hypothesis. In agreement with similar studies, I find a statistically insignificant and close to zero elasticity of supply with respect to the (after tax) wage. The "fiscal illusion" hypothesis on the part of workers was tested and rejected. In general, I found the supply side more satisfactorily determined than in past disequilibrium studies. An important caveat in the results is the questionable predeterminedness of the real (but not nominal) wage. My simple model was able to predict quite closely actual employment (within sample) and to give estimates of the extent of disequilibrium in the labour market that correlated closely with intuitive measures of the degree of "slackness" in the market.

For safer inferences on the equilibrium versus disequilibrium issue, however, evidence of a much more disaggregated nature is needed, as non-market clearing makes more sense as a micro phenomenon (see Bouissou et al. [6]). The reason that such micro-data based studies are more suited to studying the equilibrium versus disequilibrium question is that once one starts aggregating, the perpetual flux of micro disequilibria that might exist could become extremely hard to detect.

The simulation estimation method employed in this paper appears to offer considerable promise in the estimation of disequilibrium and other nonlinear econometric models with structural temporal dependence. I view this as an exciting avenue for future research.

Appendix A

Recall the model

$$D_t = \bar{D}_t + \epsilon_t = D_t^* + \eta_t + \epsilon_t \tag{1}$$

$$S_t = \bar{S}_t + u_t = S_t^* + \theta_t + u_t \tag{2}$$

$$Q_t = \min(D_t, S_t). \tag{3}$$

Define the event $\{\text{excess } S\} \equiv \{D^* - S^* + \eta - \theta < u - \epsilon \equiv \xi\}$. Further define $K \equiv D^* - S^* + \eta - \theta$. Then, $E(\epsilon|\text{excess } S, \eta, \theta) = E(\epsilon|K < \xi)$ and

$$P(\epsilon|K < \xi) \equiv \frac{P(\epsilon \cap K < \xi)}{P(K < \xi)} = \frac{\int_K^{-\infty} f(\epsilon, \xi) d\xi}{P(K < \xi)} = \int_K^{-\infty} (\epsilon, \xi) d\xi / \Phi\left(-\frac{K}{\sigma_\xi}\right). \tag{18}$$

Hence,

$$E(\epsilon|\text{excess } S, \eta, \theta) = \frac{\int_{-\infty}^{\infty} \int_K^{\infty} f(\epsilon, \xi) d\xi d\epsilon}{\Phi\left(-\frac{K}{\sigma_\xi}\right)} = \frac{\int_K^{\infty} \int_{-\infty}^{\infty} \epsilon f(\epsilon|\xi) f(\xi) d\xi}{\Phi\left(-\frac{K}{\sigma_\xi}\right)}. \tag{19}$$

Since $\begin{pmatrix} \epsilon \\ \xi \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} \sigma_\epsilon^2 & \sigma_{\epsilon\xi} \\ \sigma_{\epsilon\xi} & \sigma_\xi^2 \end{bmatrix}\right)$, we know that $E(\epsilon|\xi) = 0 + \sigma_{\epsilon\xi}\xi/\sigma_\xi^2$. Then (19) yields:

$$E(\epsilon|\text{excess } S) = \frac{\sigma_{\epsilon\xi}}{\sigma_\xi^2} \frac{1}{\Phi\left(\frac{-K}{\sigma_\xi}\right)} \int_K^{\infty} \xi f(\xi) d\xi = \frac{\sigma_{\epsilon\xi}}{\sigma_\xi} \phi\left(\frac{K}{\sigma_\xi}\right) / \left(1 - \Phi\left(\frac{K}{\sigma_\xi}\right)\right), \tag{20}$$

by noting that

$$\int_K^{\infty} \xi \ f(\xi) d\xi = \left[-\frac{1}{\sqrt{2\pi}\sigma_\xi} \exp\left(-\frac{1}{2}\frac{\xi^2}{\sigma_\xi^2}\right)\right]_K^{\infty} = \frac{1}{\sqrt{2\pi}\sigma_\xi} \exp\left(-\frac{1}{2}\frac{\xi^2}{\sigma_\xi^2}\right) \equiv \phi\left(\frac{K}{\sigma_\xi}\right). \tag{21}$$

Reversing the argument, we obtain

$$E(u|\text{excess } D, \eta, \theta) = \frac{-\sigma_{u\xi}}{\sigma_\xi} \phi\left(\frac{K}{\sigma_\xi}\right) / \Phi\left(\frac{K}{\sigma_\xi}\right). \tag{22}$$

Finally, we combine (20) and (22) into equation (5) to get equation (7).

Appendix B
Data Sources and Description of Quarterly Manufacturing Data

1. Sources: Citibank Economic Data Base [9], Council of Economic Advisors (CEA), U.S. Board of Governors of the Federal Reserve System

2. Data Series:

Name*	Description**
PRODWORM	Production workers on non-agricultural payrolls: manufacturing (thousands) (LPWM6)
AWKHRPWM	Average weekly hours of production workers: manufacturing (LPHRM6)
AHEPWM	Average hourly earnings of production workers: manufacturing ($) (LE6HM)
PPIM	Producer price index: manufactured goods (1967 = 100) (PWM)
CPIU	PI-U: all items (1967 = 100) (PZU)
WBAR	Compensation per hour employees: non-farm business sector (LBPUR) seasonally adjusted
IP	Quarterly series on industrial production, U.S. Board of Governors of the Federal Reserve System
LFCIV	Civilian labour force: total (thousands) (LHC6)
UNEM	Percent unemployed of civilian labour force, total, 16 years and over (LHUR) seasonally adjusted
YBAR	Potential GNP in real 1972 dollars (from the Council of Economic Advisors)
TB3MONTH	Interest rate: U.S. Treasury Bills, auction average, 3-month (% per annum) (FYGN3)
GPY	Personal income, current dollars
GYD	Disposable personal income, current dollars

3. Constructed Series:

Name	Definition
LE	log(PRODWORM*AWKHRPWM*52.)
W	log(AHEPWM/PPIM)
TH	1.0 - GYD/GPY
X	log(AHEPWM*(1.0-TH)/CPIU)
POTL	log(LFCIV)
RRCHAT	(1.0 + TB3MONTH)/(1.0 + CINFHAT)
RELW	(AHEPWM/WBAR) , normalized to 1. in 1977
Y	log(IP/PPIM)

Notes:

* All series are seasonally unadjusted, unless otherwise stated.

** Original CITIBASE names of variables are given in parentheses.

Table 2

Equation (7), T = 141, Dependent Variable = LE
(Asymptotic t-ratios in parentheses)

Model	**AGD**	**AGDSC**	**AGDM**	**AGDMSC**
LF	285.27	316.54	310.92	337.85
corr(LE,$\widehat{LE}$)	0.915	0.946	0.968	0.986
$\hat{\sigma}_{ED}$	0.201	0.193	0.137	0.111
	(3.656)	(2.937)	(4.993)	(4.522)
$\hat{\sigma}_{\zeta}$	—	—	0.801	0.824
			(5.372)	(6.225)
$\hat{\rho}(v_t, v_{t-1})$	—	0.873	—	—
		(8.909)		
Demand				
Constant	5.451	9.298	10.333	8.111
	(4.979)	(11.510)	(15.119)	(12.637)
Q	12.61	1.110	-0.018	-0.213
	(10.851)	(-1.655)	(-2.196)	(-2.178)
Q2	-0.026	-0.019	-0.031	-0.033
	(-1.947)	(-1.662)	(-2.783)	(-2.001)
Q3	-0.031	0.008	-0.015	-0.044
	(-2.501)	(-0.067)	(-1.249)	(-2.677)
Trend	0.007	0.008	0.007	0.009
	(5.381)	(10.531)	(11.03)	(11.237)
W	-2.133	-1.435	-1.907	-2.167
	(-3.127)	(-3.012)	(-4.176)	(-4.211)
WLAG	-0.915	-0.612	0.128	-1.017
	(-1.193)	(-1.211)	(0.281)	(-1.277)
Y	0.861	0.735	0.644	0.963
	(5.973)	(6.057)	(5.679)	(6.277)
YLAG	0.344	0.131	0.123	0.235
	(2.546)	(1.279)	(1.234)	(2.677)
$\hat{\rho}_{\eta}$	—	—	—	0.152
				(2.714)

Table 2 (continued)
Equation (7), T = 141, Dependent Variable = LE
(Asymptotic t-ratios in parentheses)

Model	AGD	AGDSC	AGDM	AGDMSC
Supply				
Constant	20.972	19.983	18.242	18.376
	(17.680)	(26.845)	(21.265)	(29.637)
Q1	-0.563	-0.038	-0.034	-0.633
	(-2.070)	(-1.204)	(-4.562)	(-2.124)
Q2	-0.019	0.053	-0.059	-0.023
	(-1.338)	(0.611)	(-2.209)	(-2.171)
Q3	-0.011	0.011	-0.043	-0.021
	(-0.336)	(1.319)	(-1.764)	(-0.379)
T	-0.018	-0.031	0.012	0.025
	(-0.584)	(-0.474)	(1.182)	(1.188)
X	1.293	0.249	-0.621	-0.621
	(1.930)	(1.180)	(-1.285)	(-1.285)
XLAG	0.342	1.193	1.351	1.266
	(0.612)	(6.425)	(2.369)	(2.885)
RELW	1.689	1.663	1.653	1.777
	(1.051)	(4.811)	(2.053)	2.261
RELWLAG	0.960	0.994	0.050	0.066
	(0.639)	(2.828)	(-0.064)	(-1.222)
POTL	1.087	0.757	1.385	1.822
	(0.999)	(2.765)	(1.356)	(2.115)
POTLLAG	-0.582	-0.880	-1.643	-1.442
	(-0.530)	(3.162)	(-1.561)	(-1.825)
RRCHAT	0.068	0.082	0.089	0.093
	(6.781)	(15.409)	(11.235)	(9.678)
$\hat{\rho}_\theta$	—	—	—	0.237
				(2.921)

Table 3

Equation (7), T = 141, Dependent Variable = LE
(Asymptotic t-ratios in parentheses)

Model	AGD	AGDSC	AGDM	AGDMSC
LF	295.36	326.71	323.94	346.43
corr(LE,$\widehat{LE}$)	0.925	0.951	0.974	0.989
$\hat{\sigma}_{ED}$	0.203	0.187	0.139	0.102
	(3.233)	(3.031)	(5.023)	(4.311)
$\hat{\sigma}_{\zeta}$	—	—	0.817	0.837
			(5.993)	(6.137)
$\hat{\rho}(v_t, v_{t-1})$	—	0.867 (9.121)		
$\hat{\rho}(LE_t, LE_{t-1})$	0.937	0.078	0.193	0.013
	(11.236)	(0.874)	(2.676)	(0.637)
Demand				
`Constant`	5.236	6.407	9.714	10.263
	(4.372)	(2.071)	(14.041)	(13.346)
`Q1`	1.182	1.113	-0.027	-0.025
	(9.629)	(-0.813)	(-2.610)	(-2.160)
`Q2`	-0.023	-0.016	-0.039	-0.031
	(-1.735)	(-1.325)	(-3.236)	(-2.834)
`Q3`	-0.027	-0.024	-0.019	-0.015
	(-2.352)	(-1.123)	(-1.677)	(-1.248)
`Trend`	0.006	0.011	0.007	0.007
	(4.992)	(3.646)	(11.566)	(9.828)
`W`	-2.018	-2.121	-3.758	-1.931
	(-3.001)	(-2.161)	(-4.313)	(-4.134)
`WLAG`	-0.978	-0.674	-1.815	-0.134
	(-1.105)	(-0.678)	(-2.094)	(-0.274)
`Y`	0.872	1.125	1.071	0.652
	(5.283)	(4.312)	(7.328)	(5.629)
`YLAG`	0.307	0.009	0.259	0.121
	(1.993)	(1.374)	(1.904)	(1.177)
`WRES`	2.769	2.931	3.993	3.762
	(3.008)	(2.993)	(3.054)	(2.821)
`XRES`	1.563	1.611	2.036	1.992
	(3.372)	(3.459)	(3.036)	(2.731)
$\hat{\rho}_{\eta}$	—	—	—	0.131
				(1.631)

Table 3 (continued)
Equation (7), T = 141, Dependent Variable = LE
(Asymptotic t-ratios in parentheses)

Model	AGD	AGDSC	AGDM	AGDMSC
Supply				
Constant	21.763	18.505	19.724	18.152
	(17.680)	(18.602)	(24.470)	(37.679)
Q1	-0.563	-0.039	-0.040	-0.034
	(-1.992)	(-1.271)	(-7.900)	(-4.693)
Q2	-0.023	-0.053	-0.004	-0.059
	(-1.236)	(-0.965)	(-0.315)	(-2.756)
Q3	-0.020	-0.041	0.006	-0.043
	(-0.221)	(-0.712)	(0.528)	(-2.132)
T	-0.023	-0.032	-0.027	-0.014
	(-0.744)	(-0.362)	(-0.351)	(-1.227)
X	1.528	0.987	-0.561	-0.628
	(1.390)	(1.606)	(-0.705)	(-1.417)
XLAG	0.368	0.352	1.989	1.360
	(0.931)	(0.581)	(2.679)	(2.771)
RELW	1.953	1.415	1.779	1.719
	(1.619)	(0.970)	(4.569)	(2.315)
RELWLAG	0.783	2.252	1.039	-0.042
	(1.273)	(0.873)	(2.728)	(-0.054)
POTL	1.291	1.281	0.755	1.391
	(0.816)	(0.691)	(2.658)	(1.732)
POTLLAG	-0.432	-1.083	-0.837	-1.678
	(-1.327)	(-0.567)	(-2.894)	(-1.983)
RRCHAT	0.096	0.079	0.084	0.087
	(4.823)	(7.632)	(14.957)	(14.307)
WRES	0.311	0.497	0.553	0.632
	(1.728)	(1.114)	(1.235)	(0.932)
XRES	0.531	0.569	1.103	0.997
	(0.562)	(0.992)	(1.113)	(1.382)
$\hat{\rho}_\theta$	—	—	—	0.201
				(1.813)

References

[1] Altonji, J.G. (1982): "The Intertemporal Substitution Model of Labour Market Fluctuations: An Empirical Analysis," *Review of Economic Studies*, XLIX.

[2] Altonji, J.G. and O. Ashenfelter (1980): "Wage Movements and the Labour Market Equilibrium Hypothesis," *Economica*, (August).

[3] Andrews, D.W.K. (1989): "An Empirical Process Central Limit Theorem for Dependent Non-identically Distributed Random Variables," *Journal of Multivariate Analysis*, v.38 (August), 187–203.

[4] Andrews, M. and S. Nickell (1986): "A Disaggregated Disequilibrium Model of the Labour Market," *Oxford Economic Papers*, v.38, 3 (November).

[5] Barro, R.J. and H.I. Grossman (1971): "A General Disequilibrium Model of Income and Employment," *American Economic Review*, 61 (March).

[6] Bouissou, M.B., J.J. Laffont and Q.H. Vuong (1986): "Disequilibrium Econometrics on Micro Data," *Review of Economic Studies*, LIII.

[7] Box, G.E.P. and G.M. Jenkins (1970): *Time Series Analysis, Forecasting and Control.* San Francisco, Holden Day.

[8] Butler, J. and R. Moffit (1982): "A Computationally Efficient Quadrature Procedure for the One-Factor Multinomial Probit Model," *Econometrica* 50.

[9] *CITIBASE: Citibank Economic Database*, New York, Citibank. 1986 Update.

[10] Eaton, J. and R. Quandt: (1983): "A Quasi-Walrasian Model of Rationing and Labor Supply," *Economica* (August).

[11] Engle, R. Hendry, D.F. and J.F. Richard (1983): "Exogeneity," *Econometrica*, January.

[12] Fair, R.C. and D.M. Jaffee (1972): "Methods of Estimation for Markets in Disequilibrium," *Econometrica*, 40 (May).

[13] Goldfeld, S.M. and R.D. Quandt (1975): "Estimation of a Disequilibrium Model and the Value of Information," *Journal of Econometrics*, 3.

[14] Gourieroux, C., A. Monfort, and A. Trognon (1984): "Pseudo Maximum Likelihood Methods: Theory," *Econometrica*, 52, 681–700.

[15] Hajivassiliou, V.A. (1984): "A Computationally Efficient Quadrature Method for the One-Factor Multinomial Probit Model," MIT mimeo.

[16] Hajivassiliou, V.A. (1985): "Disequilibrium and Other Limited Dependent Variables Models in Econometrics," unpublished Ph.D. thesis, Massachusetts Institute of Technology.

[17] Hajivassiliou, V.A. (1986): "Two Misspecification Tests for the Simple Switching Regressions Disequilibrium Model," *Economics Letters*, 22.

[18] Hajivassiliou, V.A. (1987): "An Aggregative Disequilibrium Model of the US Labour Market," Cowles Foundation Discussion Paper # 848, Yale University.

[19] Hansen, L.P. and Singleton (1982): "Generalized Instrumental Variables Estimation of Nonlinear Rational Expectations Models," *Econometrica*, 50 (September).

[20] Kooiman, P. (1984): "Smoothing the Aggregate Fix-price Model and the Use of Business Survey Data," *The Economic Journal*, December.

[21] Laffont, J.J. and A. Monfort (1979): "Disequilibrium Econometrics in Dynamic Models," *Journal of Econometrics*, 11.

[22] Lambert, J.P. (1984): "Models Macro-Economique de Rationnement et Enquettes de Conjoctures," Les Recherches Economiques de Louvain: Louvain-La-Neuve, Belgium.

[23] Laroque, G. and B. Salanié (1989). "Estimation of Multi-Market Disequilibrium Fix-Price Models: An Application of Pseudo Maximum Likelihood Methods," *Econometrica*, bf 57, 831-860.

[24] Laroque, G. and B. Salanié (1992). "Simulation Estimation of Disequilibrium Models with Serial Correlation: Theoretical and Monte Carlo Results," INSEE mimeo, presented at International Conference on Simulation, Rotterdam, The Netherlands.

[25] Lee, L.-F. (1984): "The Likelihood Function and a Test for Serial Correlation in a Disequilibrium Market Model," *Economics Letters*, V. 14, Nos. 2-3.

[26] Maddala, G. and F. Nelson (1974): "Maximum Likelihood Methods for Markets in Disequilibrium," *Econometrica*, 42.

[27] Malinvaud, E. (1980): "Macroeconomic Rationing of Employment," in E. Malinvaud and J.P. Fitoussi, *Unemployment in Western Countries*, London, MacMillan.

[28] Mankiw, N.G., J. Rotemberg and L. Summers (1985): "The Intertemporal Hypothesis in Macroeconomics," *Quarterly Journal of Economics* (February).

[29] McFadden, D. (1989). "A Method of Simulated Moments for Estimation of Discrete Response Models without Numerical Integration," *Econometrica* **57**, 995-1026.

[30] Muellbauer, J. (1978): "Macro Theory vs. Macro Econometrics: The Treatment of Disequilibrium in Macro Models," Birkbeck College Discussion Paper, 79 (April).

[31] Newey, W. and K. West (1987): "A Simple, Positive Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*.

[32] Pakes, A. and D. Pollard (1989). "Simulation and the Asymptotics of Optimization Estimators," *Econometrica* **57**, 1027-1057.

[33] Quandt, R.E. (1981): "Autocorrelated Errors in Simple Disequilibrium Models," *Economics Letters*, 7.

[34] Quandt, R.E. (1982): "Econometric Disequilibrium Models," *Econometric Reviews*, 1.

[35] Quandt, R.E. (1986): "Estimation in Disequilibrium Models with Aggregation," Financial Research Center Memorandum No. 68, Princeton University.

[36] Quandt, R. and H. Rosen (1986): "Unemployment, Disequilibrium and the Short-Run Phillips Curve: An Econometric Approach," *Journal of Applied Econometrics*, Vol.1, 235-253.

[37] Richard, J.-F. (1992): "An Acceleration Method for Simulation Estimation of Dynamic Limited Dependent Variable Models," mimeo, University of Pittsburgh.

[38] Robinson, P. (1982): "On the Asymptotic Properties of Models Containing Limited Dependent Variables," *Econometrica* (January).

[39] Romer, D. (1981): "Rosen and Quandt's Disequilibrium Model of the Labor Market: A Revision," *Review of Economics and Statistics.*

[40] Rosen, H.S. and R.E. Quandt (1978): "Estimation of a Disequilibrium Aggregate Labor Market," *Review of Economics and Statistics*, 60.

[41] Salanié, B. (1989): "Wage and Price Adjustment in a Multimarket Disequilibrium Model," *Journal of Applied Econometrics.*

[42] Sargent, T.J. (1978): "Estimation of Dynamic Labour Demand Schedules Under Rational Expectations," *Journal of Political Economy* (December).