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ONE BUSINESS CYCLE AND ONE TREND
FROM (MANY,) MANY DISAGGREGATES

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One Business Cycle and One Trend
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Abstract

Typical analyses of trends and cycles take as given some (one) observable economic variable in whose time path a researcher wishes to find trend and cyclical movements. But individual sectors and regions in aggregate economies move neither perfectly with nor independently of each other—why is their aggregate useful to study? Using a model for non-stationary, dynamically evolving distributions, this paper provides evidence that in the US, regional movements that preserve their aggregate time path nevertheless have important, predictive comovements with aggregate GNP. Such predictive content cannot be understood in traditional macro models that seek the source for business cycles in aggregate productivity or monetary shocks.

Keywords: business cycle, growth, distribution dynamics, economic fluctuation, geographical region, large cross section, stochastic kernel

JEL Classification: C33, E32, E37

* Correspondence to: D. Quah, LSE, London WC2A 2AE, UK. I owe Mervyn King a special debt for helpful conversations. I thank IIES in Stockholm for hospitality, its active seminar participants for many helpful suggestions (although with results that will appear only in a subsequent paper), and Martyna Werner for help with data. All calculations here were performed using the author's econometrics shell tSrF.

1. Introduction

As aggregate economies evolve, individual sectors and regions grow and fluctuate. Those disaggregates move neither perfectly with nor independently of each other—why then is their aggregate useful to study?

A large part of macroeconomics concerns aggregate dynamics. Thus, significant effort has been devoted to tracing out the aggregate output effects of, among others, aggregate productivity and demand disturbances, monetary and fiscal policies, human and physical capital investment, and macroeconomic, financial, and political stability.¹ Such effort ignores disaggregate dynamics. If doing so were inessential, then the study of aggregative mechanisms gives insight into economic structure. The opposite, however, would cast doubt on the usefulness of many standard macroeconomic abstractions.²

To be concrete, take as just one example regional disaggregates. The Solow residual or a monetary aggregate might well be the only aggregate disturbances we can see that are sufficiently large, volatile, and exogenous to perturb national output. But what if aggregate output could significantly fluctuate just because economic activity relocates from Galicia to Andalucia, from Lincolnshire in the East Midlands to the Greater London area, from Toscana to Veneto? By definition, *aggregate* technology or monetary disturbances cannot drive such purely redistributive fluctuations. Or, if they do, then usual models of aggregate fluctuations have misspecified the propagation mechanism, leaving out important elements of the structure of business cycles.

This argument is no more than Barro and Sala-i-Martin's (1991) for studying

¹ This list intentionally contains both the focus of studies in aggregate time series and that of studies in cross-country growth. It also clarifies that the issue here is not whether one uses only univariate or multivariate information to investigate cycles and trends in aggregate output.

² This relates closely to the arguments in King (1993); also relevant are Christiano and Eichenbaum (1992), Galor and Zeira (1993), Kirman (1992), and Long and Plosser (1983).

Solow convergence in US states, but now applied to aggregate disturbances and fluctuations. Just as US states share a common language, custom and practice, and state of technological development, so too must they share the same aggregate monetary policies and the same Solow/Prescott technology shock. Suppose that we could isolate movements in disaggregates that leave invariant their aggregate. Were aggregate disturbances the only important source of business cycles, then those disaggregate and aggregate dynamics must be related in a particular way: while aggregate fluctuations might cause disaggregate dynamics, the latter should carry no additional predictive information for the former. For instance, in the propagation mechanisms in Abraham and Katz (1986), disaggregates only react passively to aggregate disturbances. Thus, lagged disaggregates should not marginally predict future aggregate fluctuations, after conditioning on lagged aggregates. Studying such relations between aggregates and disaggregates can therefore shed light on the impulses driving business cycles.

Provided we take the right disaggregates, those empirics are of interest for not only macroeconomic debate, but also economic geography and regional analysis. Further, they would speak indirectly to policy concern in the European Community. Economists, e.g., Blanchard and Katz (1992) and Eichengreen (1990), have analyzed US states to draw economic lessons for a (hypothetically) unified Europe. Unification, in light of recent events, remains a large, complex issue; much more modest, but arguably more immediately relevant, is the question of resource redistribution within the European Community. Such redistributive policies have three important characteristics: (i) they keep member states separate countries; (ii) they are geographically concentrated within each member state; and finally, (iii) they involve a substantial amount of resources.³ Thus, they do not correspond to the usual notion of an aggregate macroeconomic shock. What impact—if any—will such actions have on the economy containing that reallocation?

³ Even if the total EC budget remains only 1.2% of Community GDP, reallocation towards the poorest “Cohesion Four” necessarily means relatively large, localized regional disturbances in those countries.

The analysis to be given below is too simplistic to hope for more than first-pass answers to the questions above. But some such analysis, possibly following the line of attack in Section 3, will be needed. Instead, the current paper might be viewed only as showing how: (i) disaggregate information can be studied econometrically in a model of dynamically evolving distributions; and (ii) insights from empirical growth and regional analysis can be used to study aggregate fluctuations. On (ii) this paper takes ideas from Barro and Sala-i-Martin (1991), Blanchard and Katz (1992), and Eichengreen (1990). It differs from them, however, in a number of ways.

First, it refuses to view regional dynamics as transitional adjustment and convergence to steady state. Instead, it follows that interpretation of stochastic equilibrium dynamics in Hansen and Sargent (1981) and Stokey, Lucas, and Prescott (1989), and treats business cycles and growth trends jointly and symmetrically. Second, the current paper is concerned not only with how particular individual regions respond to different kinds of shocks but with whether regional events as a whole carry information for, and in turn are affected by, the evolution of the aggregate economy. This goal leads to the third, methodological difference: the current paper steps outside those standard econometric approaches for the dynamics of large cross-sections which involve either taking averages in time, taking averages (groups) in the cross section, or using panel data methods.⁴ Here, the disaggregates are taken to form a cross-sectional distribution: the dynamics of interest are both intra-distributional and in the evolution of the external shape of the distribution. Conducting the usual kinds of regression analysis only gives the researcher a false sense of having larger samples than available with time series. If the cross-section were reasonably uncorrelated and homogeneous, then it might well be true that standard regression averaging gives a more precise characterization of dynamic behavior. But, even if so, it will do that *not* for the entire distribution, but only for the average or representative unit. The whole point to

⁴ I and others have argued elsewhere why these are inappropriate for the issues of interest here. See, e.g., Bernard and Durlauf (1993) and Quah (1993b–d).

the current analysis, however, is to study how aggregates affect and are affected by the distribution across disaggregates, not the cross-section’s representative element.

2. Basic Facts

Over the last complete US economic upturn (NBER trough to peak, 1982 to 1990), nation-wide nominal per capita personal income⁵ rose by 48%. At the trough, 20 states had per-capita incomes higher than the national average. Over the upturn, half of these increased their lead on that average. The best performer on this index, New Jersey, was initially already 19% richer than average. This disparity rose to 29% in 1990. Over the same upturn, again, half of the (31) states initially poorer than average increased their absolute per capita income disparities from the national average: they became even poorer. The worst performer on this index, Oklahoma, began 1% below the national average, and ended up 19% below.

In contrast to the long-run convergence found in Barro and Sala-i-Martin (1991), these facts suggest the opposite, a divergence across states. I have intentionally emphasized the business-cycle horizon here, but short-run and long-run tendencies cannot differ forever. At some “run,” the two must coincide. A standard interpretation therefore is that my numbers show only short-run business cycle fluctuations—they will average out for growth analysis. Interpreted this way, however, these numbers appear *large* relative to the typical 4–5% aggregate fluctuations about trend. Abstracting from state-specific inflations, these numbers imply 2–3% annual real business-cycle movements within a state, and, further, in *opposite* directions over an aggregate upturn.

The numbers I have chosen are extreme, and thus potentially unrepresentative. But they do display the wide range of possibilities, *and* they establish that regional disaggregates do not all move together. More important, these simple calculations

⁵ This series is constructed from the Data Appendix in Blanchard and Katz (1992). As there, *state* below refers to the 50 US States and the District of Columbia.

raise a number of additional questions. Is the lack of complete co-movement economically significant for models of economic fluctuations that theorize in terms of “the” technology shock, “the” monetary shock, or “the” aggregate demand shock? Does “the” business cycle affect one region more than another? Or is it that independent, exogenous fluctuations in one region spill over onto others, and thereby to the aggregate economy?

Should macroeconomists expend effort on theoretical models for such questions, or instead just continue with purely aggregative models? To answer this, one would like some calibration of the reliability and strength of the facts I give above. I provide one such calibration here.

3. Modelling Disaggregated/Regional Dynamics

I will take state per capita personal income relative to the national average to be due to disaggregate-specific shocks, having conditioned out aggregate effects. This is a simple scheme to identify aggregate and idiosyncratic disturbances—much simpler and more easily implemented than that in, say, Quah and Sargent (1993). No one scheme is always better or worse than another: every scheme uses different identifying assumptions, and each scheme appeals more to some than to others. Beyond ease of calculation, however, the virtue of the identification here is ease of interpretation. Alternate realizations of the distribution of relative personal incomes are just different configurations of regional activity that maintain an invariant timepath for their aggregate. If this distribution has predictive power for a different aggregate (say real GNP), then regional disaggregates contain important additional dynamics: by additional, I mean simply dynamics beyond endogenous responses to an aggregate disturbance.

A multivariate time series model is impractical to study the dynamics of many, many disaggregates. For the US, annual post-War data on states would make up a (roughly) 50-vector time series for which we might have only 40 usable observations. Even with quarterly data the ratio of observations to the dimension of the system is at most 4. Contrast this with, say, bivariate time series models (for

instance, aggregate income and consumption) where this ratio is closer to 100. For European regional analysis there are over 170 cross-sectional regions (NUTS-2 disaggregation) for which annual data are available from 1982. EC Cohesion Fund resource redistribution is planned to occur at the level of NUTS-3 subdivisions—over 800 of these are spread across the 12 EC member states.

The joint dynamics of an $(800+12)$ -vector time series are difficult to analyze. Neither is it straightforward, ahead of time, to know if it might only be selected regions that will be important to study: no theoretical model will, by itself, name New Jersey or Oklahoma or East Midlands. Further, we will see below that such an approach would turn out not to be revealing.

Instead, denote the time t cross-sectional distribution of regional disaggregates by $\mathcal{F}_t$: this distribution evolves over time, both in the relative positions of different elements of the cross-section (i.e., intra-distributionally), and in its external shape. All those dynamics are conveniently represented by a stochastic kernel equation, $\forall \mathcal{A} : \phi_t(\mathcal{A}) = \int M_t(y, \mathcal{A}) \phi_{t-1}(dy)$, where ϕ_t is the measure corresponding to $\mathcal{F}_t$, and M_t is a sequence of stochastic kernels. If $\mathcal{F}_t$ is discrete, then M_t collapses to a (Markov chain transition probability) stochastic matrix. In general, the stochastic kernel is time-varying; if not, then the transitions are said to be stationary.

Flexible time-varying stochastic kernels are difficult to estimate and analyze. In this paper, I parameterize the dynamics of the evolving distribution in $\mathcal{F}$ by a pair (M, Q) , where M is a time-invariant *fractile transition probability matrix* and $Q = \{Q(t) : \text{integer } t\}$ is a *sequence of quantiles*, $Q(t) = \{q_1(t), q_2(t), \dots, q_n(t)\}$. To construct these, fix on the open interval $(0, 1)$ a set of equal-spaced probabilities $P = \{p_1, p_2, \dots, p_n\}$. For income distribution $\mathcal{F}_t$ in period t , the set P determines a corresponding set of quantiles $Q(t) = \{q_1(t), q_2(t), \dots, q_n(t)\}$, where, by definition, $p_k(t) = \mathcal{F}_t(q_k(t))$. Each quantile-set pair $(Q(t), Q(t+1))$ defines an $(n+1) \times (n+1)$ transition probability matrix M of transitions from $\mathcal{F}_t$ to $\mathcal{F}_{t+1}$. (Note that given probabilities P , the transition probability matrix is uniquely determined even if the quantile set $Q(t)$ is not.) If the transition probability M is assumed time-invariant—done so here—then M can be estimated by appropriate

averaging. Together, (M, Q) represent a time-varying (non-stationary) evolving distribution.⁶ Notice that the resulting process represented in (M, Q) need not be stationary first-order Markov—the dynamics implied by transition probability M are compounded with those in the vector process $Q(t)$. If Q were time-invariant, then this parameterization collapses to the stochastic kernel equation above (but with M also time-invariant).

The data I use for $\mathcal{F}_t$ are (the log of) state per capita personal income relative to the national average.⁷ I experimented with n set at 2 through 5 for different (M, Q) : these showed little substantive change in the key findings of interest, so I will present only results for $n = 4$ here. The estimated fractile transition probability matrix M is given in Table 1. Note that the diagonal entries are much smaller than in similar transition probabilities for relative incomes across countries (e.g., in Quah (1993d))—US states show greater intra-distribution mobility than countries.

When M satisfies additional regularity conditions, the associated Markov chain process has a unique ergodic distribution. That ergodic distribution is uniform modulo Q , and further, is (roughly speaking) approached at a geometric rate given by M 's second largest eigenvalue. Here, however, (M, Q) will imply such behavior only if Q is time-invariant. Thus, we now turn to Q 's dynamic properties: we are interested, in particular, in their relation to aggregate fluctuations.

⁶ This is obviously not the only way to represent a non-stationary dynamically evolving distribution. The construction is, however, convenient for our purposes. It had earlier been used in Quah (1993d) to study cross-country dynamics; that paper, in turn, adapted ideas from Geweke, Marshall, and Zarkin (1986). Other representations are studied in a sequel, Quah (1993a).

⁷ As the reader will see below, this ignores the possibility that individual state per capita incomes might not cointegrate with the national average. With this many time series, systematic investigation of such issues is impractical. Informal examination of coefficients and Durbin-Watson statistics in the VARs estimated below suggest that my assumption is not egregious.

Table 1: US State Relative Per Capita Income, 1948–1990*
5-cell fractile transition probability, M ($n = 4$)

	Quantile				
	[0.2]	[0.4]	[0.6]	[0.8]	[1.0]
(410)	0.90	0.10			
(420)	0.10	0.81	0.09		
(410)		0.09	0.80	0.11	
(420)			0.11	0.83	0.05
(452)				0.06	0.94

* The cells are arrayed in increasing order, thus the lower right-hand portion of the table shows transitions from the rich to the rich. The numbers in parentheses on the right are the number of state/year pairs beginning in a particular cell. These numbers should be equal: they differ from each other by at most the number of years in the sample, due to rounding error. Entries showing 0 to two decimal places are left blank.

Table 2: Exclusion restriction (Granger causality) Marginal Significance Levels[†]

Quantile	System Lag Length			
	2	3	4	5
min	(0.19,0.36)	(0.16,0.45)	(0.58,0.70)	(0.77,0.89)
0.2	(0.58,0.69)	(0.75,0.72)	(0.77,0.59)	(0.85,0.58)
0.4	(0.62,0.62)	(0.35,0.64)	(0.47,0.39)	(0.57,0.49)
0.6	(0.77,0.13)	(0.12,0.07)	(0.77,0.05)	(0.70,0.01)
0.8	(0.15,0.87)	(0.30,0.98)	(0.82,0.95)	(0.32,0.10)
max	(0.02,0.18)	(0.01,0.33)	(0.02,0.67)	(0.05,0.36)

[†] The first number in each cell entry is the marginal significance level for excluding that quantile in the equation for real GNP growth; the second is that for excluding real GNP growth in the equation for that quantile. All VARs include a constant, and were estimated using data from 1948 through 1990.

Table 2 gives marginal significance levels for exclusion restriction (Granger causality) tests in bivariate VARs comprising real GNP growth and the quantile elements in $Q(t)$, taken one at a time. The Table shows mostly negative results with striking exceptions at quantile 0.6 and at the maximum. Aggregate real GNP growth helps to predict the dynamics of the 0.6 quantile, but not vice versa.⁸ By contrast, aggregate GNP growth does not help to predict the dynamics of the maximum of the distribution (or, strictly speaking, the top 2% of the distribution); instead, the maximum helps to predict GNP growth, even after conditioning on lagged GNP growth. It is not that any single state or region displays these characteristics: over the sample, altogether 19 different states, at different times, were at the 0.6 quantile point. Similarly, at different times, five different states were within the top 2% of the distribution, with Connecticut there the longest (17 non-successive years of 43). Using Connecticut directly instead of the maximum in Table 2’s calculations, shows marginal significance levels of only 0.96 (2 lags), 0.86 (3), 0.77 (4), and 0.87 (5) for Connecticut’s helping to predict the aggregate. Further, the transition matrix M estimated in Table 1 suggests that it is not simply measurement error generating these results—states’ relative positions do change, and quite a bit over the sample.⁹

From these calculations, I conclude that the distribution of regional incomes does interact with aggregate output, but not in any simple direct way. It is not the identity of any one state or region that is important, but, instead, the location within the overall dynamically evolving distribution. If I have correctly conditioned out the aggregate component in constructing these evolving distributions, it is a puzzle why characteristics of the distribution are thus related to aggregate GNP. Even if not, however, it is a puzzle why only certain characteristics of the distribution should have this relation. Why not all the quantiles? Or the stan-

⁸ For n other than 4, replace “quantile 0.6” by whichever quantile is closest.

⁹ The transition characteristics, represented in M , can also be permitted to be time-varying, and then similarly examined for predictive content. Again, this is investigated in the sequel, Quah (1993a).

dard deviation, or any other measure of spread? In calculations not reported here, measures of spread do almost nothing for predicting the aggregate.

4. Conclusion

This paper has documented the relation between (1) an important aggregate variable, real US GNP growth, and (2) regional movements in per capita incomes, relative to the national average. If the last accurately measure purely distributional movements—because the aggregate component has been conditioned out—then this paper has shown how such movements bear an interesting relation to aggregate fluctuations in ways not predicted by, nor well-understood in, conventional aggregative models. This relation—which should be further documented and refined—speaks to traditional focus on “the” aggregate productivity shock or “the” monetary disturbance as a source for aggregate fluctuations: it might be that no single large shock is needed to produce a lot of the aggregate business cycles that we see.

In respecting its space constraints, this paper has raised more questions than it can possibly answer or more systematically investigate. Following up those loose ends, extending this work to European regional fluctuations or to US industry-specific cycles, developing theoretical models to investigate these alternative (disaggregated) propagation mechanisms, are all manageable projects. Their implementation is currently under way.

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