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Asymmetric Shocks among U.S. States

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Abstract: This paper applies a factor model to the study of risk sharing among U.S. states. The factor model makes it possible to disentangle movements in output and consumption due to national, regional, or state-specific business cycles from those due to measurement error. The results of the paper suggest that some findings of the previous literature which indicate a substantial amount of interstate risk sharing may be due to the presence of measurement error in output. When measurement error is properly taken into account, the evidence points towards a lack of interstate smoothing.

JEL classification: E20, E32, F36

Key words: intranational business cycles, risk sharing, factor models

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1 Introduction

Are intranational business cycles different from international business cycles? Is there more risk sharing within a country or among countries? The trend towards trade and capital market integration observed in the past twenty years makes these questions very relevant for international macroeconomics. Indeed, the study of intranational business cycles may shed light on the future patterns of international co-movements, assuming that such a trend will continue. As a result, a growing body of literature has investigated these questions since the beginning of the nineties.[1]

The policy implications of this literature are far reaching. If risk sharing is one of the beneficial effects of a global capital market, opening internal capital markets to foreign capital may increase macroeconomic stability in the long run. For Europe in particular, the comparison between an established monetary union (United States) and a nascent one (EMU) is often used as a tool to judge the likelihood of success of the latter.[2]

Hess and Shin (1998) provide an interesting study of intranational business cycles within the United States.[3] Using data on retail sales of non-durables for nineteen U.S. states from 1978 to 1992 they show that the so-called "quantity anomaly", i.e., the finding that de-trended consumption is less correlated across countries than output (see Backus, Kehoe, and Kydland 1992), holds true at the intranational level as well. This result is interpreted as evidence of lack of risk sharing among U.S. states, since under perfect risk sharing consumption should be perfectly correlated across states.

The results of Hess and Shin are starkly at odds with those obtained by Asdrubali, Sørensen, and Yosha (1996). In an influential paper, Asdrubali et al. find that the amount of risk sharing among U.S. states is substantial: about 75% of output shocks are smoothed via either capital and credit markets or the federal government. Their finding was later confirmed by studies of Crucini (1998) and Mélitz and Zúmer (1999). While Hess and Shin and Asdrubali et al. reach opposite conclusions on the degree of inter-state risk sharing, their results are not directly comparable. Hess and Shin's data set includes only nineteen states, while the study of Asdrubali et al. includes all fifty states. Several of the thirty-one states not included in Hess and Shin's analysis, being oil producing or agricultural states, are generally subject to more risk than the nineteen considered by Hess and Shin. Perhaps more importantly, Hess and Shin's results are based on the study of cross-state correlations in consumption and output. The study of cross correlations has a serious limitation, especially when applied to state level data. Given that consumption data is likely to be measured with error, cross-state consumption correlations may be low for reasons other than lack of risk sharing.

This paper contributes to the study of intranational risk sharing in the United States in two ways. The first contribution consists in expanding Hess and Shin's data set both cross-sectionally and in the time dimension. Using a different source of data for consumption of non-durables, the paper can reproduce Hess and Shin's finding for all fifty states from 1969 to 1995. The second contribution consists the application of a factor model to the study of risk sharing. The factor model makes it possible to disentangle movements in the data due to shocks in "true" consumption and output from those purely due to measurement error. The paper finds that when measurement error in the data is taken into account, the "quantity anomaly" still holds for U.S. states, contradicting the conclusions of Asdrubali et al. In essence, the results of this paper indicate that some of the smoothing found by Asdrubali et al. may be simply shedding of measurement error in output, and not actual risk sharing.

The remaining of the paper is as follows. Section 2 discusses the model. Section 3 illustrates the data. Section 4 describes the findings of the paper, and section 5 concludes.

2 The model

This section describes the factor model which is used to analyze fluctuations in relative per capita output and consumption at the state level. By definition a change in relative per capita output or consumption in a given state implies that per capita output or consumption in that particular state does not move in synchrony with aggregate per capita output or consumption, so I will refer to these changes as "asymmetric shocks". The factor model considered here differs from the standard factor model due to the restrictions imposed in order to identify the model. The restrictions are as follows: for each state, changes in relative output and consumption are assumed to depend on nation-wide shocks (U.S. business cycle), on a regional shocks (regional business cycle), on a state-specific shocks (state-specific business cycle). The identification restrictions therefore consist of a set of zero restrictions on the matrix of coefficients: the impact of a regional business cycle shock in a given region is constrained to be zero for states which do not belong to that region, and the impact of a state-specific shock on the consumption or output of other states is also zero by assumption.[4]

The model can be described as follows. Let the variables c_{it} and y_{it} represent de-trended and de-meaned relative per capita consumption and output for state i in period t ($i = 1, ., n$; $t = 1, .., T$). Specifically, if C_{it} and C_{it}^{us} denote per capita consumption in state i and in the US, respectively, c_{it} represents the quantity $log(C_{it}) - log(C_{it}^{us})$, de-trended and de-meaned.[5] The variable c_{it} is referred to as an "asymmetric shock" in consumption, as it measures the extent to which $log(C_{it})$ and $log(C_{it}^{us})$ do not move in unison. The same definition applies to y_{it}. If state i belongs to region r $(r = 1, .., \overline{r})$, c_{it} and y_{it} are affected by the nation-wide shock f_t^{us}, by the regional shock f_t^r, and by the state-specific shock f_t^i. In addition, consumption is affected by a purely idiosyncratic shock ε_{it}, which reflects preference shocks and/or measurement error. Relative consumption and output in each state can be affected differently by national, regional, and state specific-shocks, i.e., the exposures are not constrained to be the same. Formally, the model is as follows:

$$\begin{aligned} y_{it} &= \beta_{yi}^{us} f_t^{us} + \sum_{r=1}^{\overline{r}} \beta_{yi}^r f_t^r + \sum_{j=1}^{n} \beta_{yi}^j f_t^j \\ c_{it} &= \beta_{ci}^{us} f_t^{us} + \sum_{r=1}^{\overline{r}} \beta_{ci}^r f_t^r + \sum_{j=1}^{n} \beta_{ci}^j f_t^j + \varepsilon_{it}, \end{aligned} \tag{1}$$

where the βs denote the exposures of relative consumption and output in state i to the different factors (national - us, regional - r, etc.), and where the identifying restrictions on the exposures are as follows:

$$\begin{aligned} &\beta_{yi}^r = \beta_{ci}^r = 0 \text{ if state } i \text{ does not belong to region } r \\ &\beta_{yi}^j = \beta_{ci}^j = 0 \text{ for all } j \neq i. \end{aligned} \tag{2}$$

The factors are, by construction, uncorrelated with each other and with the idiosyncratic shocks, and the idiosyncratic shocks are also uncorrelated with each other:

$$\begin{aligned} E[f_t^{us} f_t^r] &= E[f_t^{us} f_t^i] = E[f_t^{us} \varepsilon_{it}] = 0, \\ E[f_t^r f_t^s] &= E[f_t^r f_t^i] = E[f_t^r \varepsilon_{it}] = 0, \\ E[f_t^i f_t^j] &= E[\varepsilon_{it} \varepsilon_{jt}] = 0, \end{aligned} \tag{3}$$

for all t, all r, all i, all $s \neq r$, all $j \neq i$. It is also assumed, as in the standard factor model, that all variables are normally distributed. In particular, for all t, r, and i,

$$f_t^{us} \rightsquigarrow N(0,1),\ f_t^r \rightsquigarrow N(0,1),\ f_t^i \rightsquigarrow N(0,1),\ \varepsilon_{it} \rightsquigarrow N(0,\phi_i^2). \tag{4}$$

The assumption that factors have unitary variance is purely a normalization assumption: the different variances of U.S., regional, and state-specific business cycles are reflected in the different magnitudes of the parameters β's.

Model (1) allows for measurement error in consumption but not in output. The state-specific factor indeed coincides with the shocks to output in state i, after taking into account national and regional business cycle shocks. This assumption is made because with only two observations for each state (consumption and output) it is not possible to separately identify state-specific and idiosyncratic shocks in output. The assumption of no measurement error in output is implicitly made in some of the previous literature as well (Asdrubali et al. and Mélitz and Zúmer): as these authors use output as a regressor, the presence of substantial measurement error in output would indeed imply that their estimates contain a bias. While these assumption is generally thought to be reasonable, as output is likely to be better measured than consumption, the results in section 4 show that it may not be correct.

When two different measures for consumption and output are available, the factor model can be used to quantify the amount of measurement error attributable to *both* output and consumption. Let us call y_{it}^1 and y_{it}^2, and c_{it}^1 and c_{it}^2, the two available measures of relative output and consumption in state i at time t, respectively. Shocks to y_{it}^1 and y_{it}^2 (c_{it}^1 and c_{it}^2) are the result of shocks in the "true" measure of relative output (consumption), which is unobservable, and of measurement error. Formally:

$$\begin{aligned} y_{it}^1 &= y_{it}^* + error_{it}^{y1}, \\ y_{it}^2 &= y_{it}^* + error_{it}^{y2}, \\ c_{it}^1 &= c_{it}^* + error_{it}^{c1}, \\ c_{it}^2 &= c_{it}^* + error_{it}^{c2}, \end{aligned} \tag{5}$$

where y_{it}^* and c_{it}^* are the "true" measures of output and consumption, respectively. As in model (1), I assume that movements to y_{it}^* and c_{it}^* can be attributed to national, regional, and state-specific shocks, as well as preference shocks in the case of consumption. Under these assumptions, model (1) can be extended as follows:

$$\begin{aligned} y_{it}^1 &= \beta_{yi}^{us} f_t^{us} + \sum_{r=1}^{\bar{r}} \beta_{yi}^r f_t^r + \sum_{j=1}^{n} \beta_{yi}^j f_t^j + \gamma_{yi} f_t^{yi} + \varepsilon_{it}^{y1}, \\ y_{it}^2 &= \beta_{yi}^{us} f_t^{us} + \sum_{r=1}^{\bar{r}} \beta_{yi}^r f_t^r + \sum_{j=1}^{n} \beta_{yi}^j f_t^j + \gamma_{yi} f_t^{yi} + \varepsilon_{it}^{y2}, \\ c_{it}^1 &= \beta_{ci}^{us} f_t^{us} + \sum_{r=1}^{\bar{r}} \beta_{ci}^r f_t^r + \sum_{j=1}^{n} \beta_{ci}^j f_t^j + \gamma_{ci} f_t^{ci} + \varepsilon_{it}^{c1}, \\ c_{it}^2 &= \beta_{ci}^{us} f_t^{us} + \sum_{r=1}^{\bar{r}} \beta_{ci}^r f_t^r + \sum_{j=1}^{n} \beta_{ci}^j f_t^j + \gamma_{ci} f_t^{ci} + \varepsilon_{it}^{c2}, \end{aligned} \tag{6}$$

where the identifying restrictions on the βs, as well the distributional assumptions, are the same as in model (1). The term $\gamma_{ci} f_t^{ci}$ allows for the presence of preference shocks in consumption, and for the possibility that the measurement errors in the consumption data are correlated. The term $\gamma_{yi} f_t^{yi}$ allows for the possibility that the measurement errors in the output data are correlated. The relative accuracy of the different data sets can be assessed by comparing the standard deviations of the idiosyncratic errors, ε_{it}^{y1} and ε_{it}^{y2} for output, and ε_{it}^{c1} and ε_{it}^{c2} for consumption.

As discussed in the next section, two different measures of non durable consumption are not available for all fifty states. Two measures of output are however available. If we modify model (6) as follows:

$$\begin{aligned} y_{it}^{1} &= \beta_{yi}^{us} f_t^{us} + \sum_{r=1}^{\overline{r}} \beta_{yi}^{r} f_t^{r} + \sum_{j=1}^{n} \beta_{yi}^{j} f_t^{j} + \gamma_{yi} f_t^{yi} + \varepsilon_{it}^{y1}, \\ y_{it}^{2} &= \beta_{yi}^{us} f_t^{us} + \sum_{r=1}^{\overline{r}} \beta_{yi}^{r} f_t^{r} + \sum_{j=1}^{n} \beta_{yi}^{j} f_t^{j} + \gamma_{yi} f_t^{yi} + \varepsilon_{it}^{y2}, \\ c_{it} &= \beta_{ci}^{us} f_t^{us} + \sum_{r=1}^{\overline{r}} \beta_{ci}^{r} f_t^{r} + \sum_{j=1}^{n} \beta_{ci}^{j} f_t^{j} + \varepsilon_{it}^{c}, \end{aligned} \tag{7}$$

we obtain a model that still allows for measurement error in both consumption and output, *and* can be estimated for all fifty states. The only substantial difference between models (6) and (7) is that the second model will not provide any information on the importance of preference shocks in consumption, as opposed to pure measurement error. The appendix describes the details of the maximum likelihood estimation of models (1), (6), and (7).[6]

From any of the three factor models described above, it follows that the standard deviation of asymmetric shocks to "true" output and consumption in state i can be expressed as:

$$\begin{aligned} stdev(y_{it}) &= \sqrt{\beta_{yi}^{us\ 2} + \beta_{yi}^{r\ 2} + \beta_{yi}^{i\ 2}}, \\ stdev(c_{it}) &= \sqrt{\beta_{ci}^{us 2} + \beta_{ci}^{r\ 2} + \beta_{ci}^{i\ 2}}, \end{aligned} \tag{8}$$

where, in order to simplify the notation, we denote by r the region to which state i belongs. Asymmetric shocks may arise from differences among states in the exposure to the U.S. business cycle, as well as from regional and state-specific business cycles.[7]

The approach developed in this section presents a number of advantages over simple correlations as a tool for studying co-movements among output and consumption across states. First of all, this methodology can quantify the size of asymmetric shocks. The correlation between two variables only conveys information on the extent to which the shocks affecting the variables are orthogonal to each other, but says nothing of the magnitude of the shocks. More importantly, the factor model makes it possible to disentangle asymmetries in consumption and output due to "true" asymmetric shocks, as opposed to asymmetries due to measurement error or preference shocks.[8]

The approach adopted here also presents an advantage over that followed by Asdrubali et al. and Mélitz and Zúmer. In essence, these authors assess the amount of interstate risk sharing via a panel regression of relative consumption on relative output. Their approach takes fully into account measurement error in consumption, the regressand, but not in output, the regressor. Models (6) and (7) have the advantage that they can allow for measurement error in both consumption and output. In addition, the decomposition of consumption and output fluctuations into national, regional, and state specific business cycles can be helpful in identifying the sources of imperfect risk sharing.

Two important assumptions underlie the model. The first assumption is that the model is not dynamic, in that the factors are assumed to be uncorrelated over time. Several papers (see Stockman 1988, and Costello 1993) neglect serial correlation when dealing with annual data. Since the model is applied to *relative* output and consumption, serial correlation in the data is even less of a problem, as discussed in the next section.[9] The second assumption is that the parameters are not time-varying. As the productive structure of the states has changed over time, so have in principle the exposures to national, regional, and state-specific business cycles. The limited time series dimension of the sample (at most 26 observations) makes it hard to deal with this issue. Therefore, I follow most previous work, and do not allow for time-varying parameters.

3 The data

The literature on risk sharing among U.S. states has used different data sets for state consumption and output. As discussed in the introduction, the literature has reached different conclusions on the extent to which U.S. states share risk. In order to assess whether this is the result of differences in the data sets, as opposed to differences in the methodology, this paper uses four data sets, which are described in table **??**.

The first data set -*data set 1 (HS)*- is, essentially, the same one used by Hess and Shin. As a measure of real output, Hess and Shin use data on real gross state product (gsp) from the Bureau of Economic Analysis (BEA). The real gsp data are available since 1977 only. They are obtained by deflating nominal gsp by a gsp deflator. The latter is a weighted average of national producer prices, where the weight of each commodity is given by its production share in each state. In terms of the consumption data, Hess and Shin argue that evidence on the "quantity anomaly" should be obtained using data on consumption of non-durables, as this variable is a better empirical counterpart to the theoretical definition of consumption used in Backus et al. (1992) than total consumption, which includes consumption of durables. As a measure of non-durable consumption Hess and Shin use retail sales of non-durables from the Bureau of the Census. These data are available only from 1978 to 1995 for nineteen states, and are no longer produced. In order to obtain real consumption, Hess and Shin deflate the data using the gsp deflator from the BEA. This paper does not follow their choice for two reasons. First, the prices used in the deflator are national prices, and do not take into account price differences within the United States.[10] Secondly, the share of any particular commodity in production is likely to be different from the share in consumption, particularly for oil producing and agricultural states. Instead, nominal consumption data are here converted into real terms using state CPI data, which are described below. This difference does not affect the results in terms of cross-state correlations in consumption and output, as discussed in the next section. In spite of this minor difference, I will refer to this data set as the HS data set.

The second data set -*data set 2 (ASY)*- is the one used by Asdrubali et al. Asdrubali et al. use as output measure the nominal gsp from the BEA. Consumption is measured as the sum of total private consumption and state and local government consumption. Total private consumption by state is obtained by multiplying total retail sales by state for the ratio of total private U.S. consumption over total U.S. retail sales for the corresponding year. Total retail sales by state are obtained from Sales&Marketing Management (the data are proprietary, and I am grateful to Sales&Marketing Management for giving me permission to use them). State and local government consumption is constructed following the definition given in their paper. Asdrubali et al. assume that there are no differences in either gsp or consumption deflator among U.S. states. Under this assumption, the presence of fixed time effects in their estimation procedure implies that the regressions can be run using nominal data, as the common deflator would be washed out by the fixed time effects. This is the case also in the factor model used here, since it applies to *relative* consumption and output. When computing cross-state correlations in consumption and output, however, I deflate nominal consumption by the U.S. CPI, obtained from the Bureau of Labor Statistics, and nominal gsp by the U.S. gdp deflator, obtained from the BEA. The time period used by Asdrubali et al. is 1963-1990. For comparison with the other data sets I use the time period 1969-1995. The data are available for all 50 states.

The third data set -*data set 3*- extends the Hess and Shin data set both cross-sectionally and in the time dimension. Like in the data set 1 (HS), nominal consumption is measured as non-durable retail sales. Since the Census data are available for nineteen states only, and only from 1978, we use Sales&Marketing Management data, which are available for all 50 states from the 1930s. Non-durable retail sales are constructed as the difference between total retail sales and retail sales of automobiles, furniture, building materials and hardware.[11] Nominal output is measured as nominal gsp from the BEA. Both consumption and output are deflated using state CPI data. The CPI series are constructed using American Chamber of Commerce Association data on Cost of Living by metropolitan areas, as well as other sources, and are weighted for each state using BEA data on population by metropolitan area. The CPI data are constructed from 1969 to 1995, which implies that the real output and consumption series are available for this period only (details on the construction of the CPI series can be found in Del Negro 1998b). When the consumption and output series are deflated using the U.S. CPI and by the U.S. gdp deflator respectively, instead of the state CPI, I obtain very similar results, which I do not report.

Since it may not be appropriate to deflate the nominal output series by the CPI, given that output and consumption baskets differ, I also present the results for a forth data set -*data set 4*- in which real output is measured as real gsp from the BEA (same source as in data set 1). Real consumption is measured as in data set 3, which makes it possible to include all 50 states in the data set. This data set covers a shorter time span than data set 3 (1978-1995), given the constraint on the availability of real gsp data.

In all data sets retail sales are used as a proxy for consumption, given that no data for state level consumption is available. Retail sales is an imprecise measure of consumption, both because it does not incorporate consumption of services, and because it may include purchases made by residents of other states.[12] However, Hess and Shin show that at the aggregate level Census retail sales are a good proxy for consumption, especially at the annual frequency.

In all data sets, the data are transformed in per capita terms using the population data from the BEA. The definition of regions used in the factor model follows the BEA. The BEA regions are New England, Mid East, Great Lakes, Plains, South East, South West, Rocky Mountains, and Far West.

As mentioned in the previous section, the factor model adopted here ignores serial correlation in the data. Table 2 provides a justification for this assumption, as it shows that the average first order serial correlation in relative consumption is nil, and is significantly different from zero at the 5% level for less than 12% of all states. The autocorrelation in relative output is higher, but with the exception of data set 2 (ASY) it is still significantly different from zero only for less than 26% of all states. For data set 2 (ASY) the first order serial correlation coefficient is significant for, at most, 40% of all states. Some authors (for instance Stockman 1988) overcome the issue of serial correlation by running a regression using the residuals from an AR process. Given the fact that the AR coefficients are imprecisely estimated, I chose not to do so, as this procedure may introduce considerable measurement error.

The data are de-trended using two different methods: log-differences (growth rates) and Hodrick-Prescott (HP) filtering. Given that the frequency of the data is annual, in applying the HP filter the smoothing parameter is set to 10 (see Baxter and King 1999).

4 The results

The discussion of the results begins with an analysis of cross-correlations for U.S. states, and continues with the description of the results of the factor models.

Table 3 displays the average cross-state correlation of consumption and output, the difference between the two, and the percentage of observations for which the correlation in output is larger than the correlation in consumption. The results are displayed for all four data sets described in the previous section, and for both detrending methods. Fig. 1 displays the cross-correlations of output and consumption across U.S. states for all four data sets. Specifically, the plots in Fig. 1 display all the pairs ($Corr(y_{it}, y_{jt})$, $Corr(c_{it}, c_{jt})$), with output correlations on the horizontal axis, and consumption correlations on the vertical axis. While Fig. 1 shows the results for the log-differenced data only, the results for the HP-detrended data are very similar, as can be seen from table 3.

The main message from table 3 and from Fig. 1 is that the "quantity anomaly" holds for U.S. states regardless of the data set. For data set 1 (HS), 94% of the observations are below the 45 degree line, implying that for almost all states consumption correlations are lower than output correlations. The average consumption correlation is between .3 and .33, and the average output correlation is between .7 and .78, depending on the de-trending method. These figures are roughly the same ones reported by Hess and Shin. For the other data sets the evidence in favor of the "quantity anomaly" is not as stark, as the introduction of thirty-one more states in the sample, many of which are agricultural and oil producing, causes a decrease in output correlations. Yet for all data sets the correlation in output is higher than the correlation in consumption for at least three quarters of the observations: the "quantity anomaly" holds for U.S. states as well as for countries. However, if low consumption correlations are due to preference shocks or measurement error, no meaningful inference can be made about risk sharing. The models described in section 2 provide a better tool to analyze the data, as they separate out measurement error in consumption and output.

Table 4 analyzes the standard deviations of asymmetric shocks in consumption and output for all data sets and detrending methods, obtained from model (1). In particular, the table shows the average standard deviations of asymmetric shocks in consumption and output across states, the difference between the two, and the percentage of observations for which the standard deviation of asymmetric shocks in consumption is larger than the standard deviation of asymmetric shocks in output, considering all states, and considering only those states for which the difference is significantly different from zero at the 95% level (in parenthesis). For each data set and detrending method, the table displays the results including (first line) and excluding (second line) idiosyncratic shocks in consumption. Note that asymmetric shocks to consumption, when purged from measurement error and/or preference shocks, are by construction related to shocks in output. One can then gauge the amount of the inter-state smoothing of output shocks by comparing the standard deviation of asymmetric shocks in output and consumption. It is important to bear in mind that the results shown in table 4 are obtained assuming that output is measured without error.

Three facts emerge from table 4. The first fact is that whenever the idiosyncratic component of consumption is included, the analysis based on correlation and the analysis based on standard deviations of asymmetric shocks deliver the same result: output is more correlated across states (less asymmetric) than consumption. For all data sets and detrending methods the standard deviation of asymmetric shocks in output is less than the standard deviation of asymmetric shocks in consumption for at least 86% of states.

The second fact is that taking idiosyncratic shocks into account makes a substantial difference. The average difference between the asymmetric standard deviation in consumption and output is halved for data set 1 (HS), more than halved for data set 4, and is completely reversed for data sets 2 (ASY) and 3. One can appreciate graphically in Fig. 2 the effect of excluding the idiosyncratic component of consumption. Fig. 2 plots the pairs of standard deviations of asymmetric shocks for non-durable consumption and output for all four data sets, with (left column) and without (right column) the idiosyncratic component of consumption (Fig. 2 focuses on log-differenced data; the plots for HP-filtered data are similar). For all the observations that lie below the 45 degree line the standard deviation of asymmetric shocks in consumption is larger than the standard deviation of asymmetric shocks in output. The starred observations are those for which the two are different at the 5% significance level. For data set 2 (ASY) and 3 the effect of excluding the idiosyncratic component is very evident: while for the plots in the left column the vast majority of the observations lies to the right of the 45 degree line, in the corresponding plots in the right column most states (and most significant observations) flip over the other side of the line.

The third fact from table 4 is that there are important differences among the data sets in terms of the implications for interstate risk sharing. For data sets 1 (HS) and 4 the "quantity anomaly" clearly holds, even after taking into account measurement error and preference shocks in consumption. For data set 1 (HS) the asymmetric standard deviation in output is *smaller* than the one in consumption for all observations for which the difference is significant. For data sets 2 (ASY) and 3, conversely, the asymmetric standard deviation in output is *greater* than the one in consumption for all observations for which the difference is significant (with the exception of HP-filtered data for data set 3). For data set 2 (ASY), in the case of log-differenced data (the one considered by Asdrubali et al.), about a third of output shocks are smoothed. This figure is not nearly as large as the 75% suggested by Asdrubali et al., perhaps because of the differences in the methodologies, but suggests a considerable amount of smoothing. Under different detrending methods and data sets the amount of smoothing is not as large.

What is driving these differences? There are three possible explanations for the divergence in the results: the number of states included in the data (nineteen versus fifty), the time period (1978-1995 versus 1969-1995), and the data sources. Differences in the number of states and in the time period explain some of the divergence in the results.[13] Much of this divergence, however, is due to differences in the data sources. When the model is estimated for data set 3 using the same time period and the same set of states as Hess and Shin, the degree of inter-state smoothing is found to be significant (the results are not shown for lack of space).

As the differences in the data sources appear to matter, one is left with the question of which data set is most reliable. Since model (1) allows for measurement error in consumption, it is unlikely that differences in the measurement of consumption are driving the results. Rather, one should focus on measurement error in output. In this regard, the data sets can be compared by looking at the standard deviation of y_{it} for the same states and the same time period. For log-differenced data, the average standard deviation of y_{it} for all fifty states in the 1978-1995 time period is 2.61%, 2.67%, and 2.23% for data sets 2(ASY), 3, and 4, respectively. For HP-filtered data, the corresponding figures are 1.7%, 1.75%, and 1.37%. These numbers point at substantial differences in the measurement of output across data sets, and imply that one needs to address the issue of measurement error in output in order to properly estimate the amount of inter-state risk sharing. Models (6) and (7) can be used to address this issue. For the nineteen states for which the BEA nondurable consumption measures are available, we can use model (6) to compare the Hess and Shin measures of output and consumption (data set 1) with those in data sets 2 (ASY) or 3.[14] Model (6) cannot be estimated for all 50 states, since only one measure of nondurable consumption is available, the one from Sales&Marketing Management. Using model (7) we can still compare the measure of output used by Hess and Shin - the real output from the BEA (data set 4)- with the nominal BEA output figures, deflated using either the US gdp deflator (data set 2-ASY) or the state-level CPI (data set 3).

Table 5 shows that measurement error in output explains the differences in the results shown in table 4. Table 5 displays the average across states of the estimated standard deviations of asymmetric shocks to consumption and output, with and without measurement error.[15] Once measurement error in *both* consumption *and* output is taken into account, the results are consistent across data sets: for at least 78% of the states the standard deviation in asymmetric shocks in consumption is larger than the standard deviation of asymmetric shocks in output. Fig. 3 complements table 5 graphically: the figure plots the standard deviations of asymmetric shocks to consumption and output, with and without measurement error, for the log-differenced data only. For all data sets, the vast majority of observations lies below the 45 degree line, both before and after considering measurement error in the data. It is important to remark that only for a handful of states the difference between the standard deviation of asymmetric shocks in consumption and output is significantly positive. The evidence towards *dis*-smoothing is weak. At the same time, there is no evidence at all pointing towards smoothing of asymmetric shocks in output. In this sense, the results unequivocally point towards a lack of risk sharing among states.

A comparison of tables 4 and 5 reveals that the results from model (1) do not always coincide with those of models (6) and (7). The average standard deviation of "true" asymmetric shocks in consumption for data set 4 should in principle be the same in table 4 and in table 5. Yet in table 4 the estimated average standard deviation of asymmetric shocks in consumption for data set 4, without measurement error, is 2.55% for log-differenced data. The corresponding measure in table 5 is 3.23% when data set 4 is paired with data set 2 (ASY), or 3.3% when is paired with data set 3. Similar differences arise for HP-filtered data. These differences are likely to be due to the very short sample (17 observations for each state), which implies that the parameters are imprecisely estimated. However, this problem does not arise for other data sets. For data set 1, for instance, the average standard deviation of "true" asymmetric shocks in consumption is roughly the same in tables 4 and 5. Since the results in terms of risk sharing are robust across data sets in table 5, the differences between tables 4 and 5 may not be much of a concern.

Table 6 provides information on the source of asymmetric shocks. For each of the measures of consumption and output used in the estimation, table 6 displays the cross sectional average of the estimated standard deviation of asymmetric shocks due to each factor (national, regional, state-specific, common measurement error, and idiosyncratic measurement error) as well as the percentage of states for which this is significantly different from zero at the 5% level.[16] In order to understand the sources of asymmetric shocks it is useful to focus on the estimates from data sets 2 (ASY) and 4, and 3 and 4, as they involve all fifty states. Estimates involving nineteen states only may not correctly identify the role of national and regional business cycles.

As far as output is concerned, national, regional, and state-specific shocks have roughly the same importance. On average, the asymmetric standard deviation of asymmetric shocks due to national business cycles is about 1% for log-differenced data, and is significantly different from zero at the 5% level for almost half of the states. For HP-filtered data, its importance relative to regional and state-specific business cycles is slightly less, but is still significantly different from zero for a third of the states. This finding implies that national business cycles have a significantly different impact across states. The finding is in contrast to the results obtained by Blanchard and Katz (1992) using employment data. Regional business cycles are as, or slightly more, important than national shocks, depending on the de-trending method, and are also significant for over

40% of states. Regional business cycles may reflect the geographical pattern of industry composition across states. The impact of state-specific shocks is as large as the impact of regional shocks in terms of magnitude, but is much more imprecisely estimated. As far as consumption is concerned, state-specific shocks seem to play a more important role than either national or regional shocks. The impact of state-specific business cycles on consumption is more than twice as large as its impact on output, indicating that the dis-smoothing with respect to state-specific shocks may be one of the major causes of the lack of risk sharing. In general, these coefficients are also very imprecisely estimated. If we focus only on those states for which the difference in the standard deviations of asymmetric shocks in consumption and output is significantly positive, the exposure of consumption to state-specific shock is large and precisely estimated. For those few states, however, the standard deviation of the idiosyncratic measurement error in consumption is estimated to be very small, which is surprising given that on average it is estimated to be large, above .87%. This suggests that for these states a large idiosyncratic movement in consumption may be mistaken for a state-specific shock.[17] In summary, the evidence suggesting that asymmetric shocks in consumption are *larger* than asymmetric shocks in output is questionable. At the same time, there is no evidence at all that points towards inter-state smoothing of asymmetric shocks in output, regardless of their source.

The figures in table 6 also help to explain why the different data sets used in table 4 sometimes lead to opposite conclusions in terms of the "quantity anomaly". The explanation lies in measurement error in output, which is sizable for data sets 2 (ASY) and 3. Model (1) allowed only for measurement error in consumption. When measurement error in consumption was taken into account in the computation of the standard deviation of asymmetric shocks, the standard deviation of asymmetric shocks in consumption decreased, but the standard deviation of asymmetric shocks in output by construction remained the same. For those data sets for which measurement error in output is relatively small, like data sets 1 and 4, the standard deviation of asymmetric shocks in consumption remained above that of output for most states. But for those data sets for which measurement error in output is large, like data sets 2 (ASY) and 3, eliminating measurement error *only* in consumption resulted in a reversal of the ranking.

Tables 6 is also informative in regard to the magnitude of preference shocks. The term $\gamma_{ci} f_t^{ci}$ in model (6) represents both common measurement error in consumption, and preference shocks. Under the assumption that measurement error and preference shocks are uncorrelated, the standard deviation of asymmetric shocks due to $\gamma_{ci} f_t^{ci}$ - the second-to-last column in table 6 - represents an upper bound on the standard deviation of asymmetric shocks due to preference shocks. Table 6 shows that the standard deviation of asymmetric shocks due to the term $\gamma_{ci} f_t^{ci}$ is fairly small on average and not significantly different from zero in all but a few cases.

In conclusion, when measurement error in both consumption and output is properly taken into account, asymmetric shocks in consumption are as large as asymmetric shocks to output for all but a few states, pointing towards a lack of inter-state smoothing. This finding is consistent with that of Hess and Shin, who show that for the nineteen states included in their analysis the "quantity anomaly" appears to hold: output is more correlated across states than consumption. The analysis of Hess and Shin, which is based on cross correlations, is affected by the problem of measurement error. However, their approach treats measurement error in output and consumption symmetrically. In contrast, the approach of Asdrubali et al. takes full account of measurement error in consumption, but does not allow for measurement error in output. According to the results of this paper, this may be why Asdrubali et al. find substantial risk sharing and Hess and Shin find none.

5 Conclusions

The paper uses a factor model to analyze asymmetric shocks to consumption and output across U.S. states. The factor model represents a particularly useful tool for the analysis of state-level data as it makes it possible to disentangle movements in output and consumption due to national, regional, or state-specific business cycles from those due to measurement error. Given that measurement error is likely to be substantial for state level data, this approach has an edge over those used in the existing literature.

The results of the paper suggest that the findings of Asdrubali et al. (1996) and Mélitz and Zúmer (1999) indicating a substantial amount of inter-state risk sharing may be due to the presence of measurement error in output: part of the smoothing of output shocks found by those authors may simply represent shedding of measurement error, and not actual risk sharing. In general, the presence of measurement error in output implies that their methodology may not be appropriate, since the use of output as a regressor may yield biased estimates of the amount of smoothing.

When measurement error in both consumption and output is properly taken into account, asymmetric shocks in consumption are as large as asymmetric shocks in output for all but a few states, pointing towards a lack of inter-state smoothing.

These results open a number of questions for future research. Firstly, this paper does not investigate the role of capital markets, credit markets, and the federal government, in smoothing or dis-smoothing asymmetric shocks to output. It would be interesting to repeat the analysis performed in the seminal paper of Asdrubali et al. taking into account measurement error in output. Secondly, the apparent lack of risk sharing at the state-level is a puzzle that needs to be explained. Recent works of Coval and Moskowitz (1997), Huberman (1999), and Hess and Shin (1999) provide direct and indirect evidence of financial market segmentation within the United States. Yet, one would think that the degree of domestic financial market segmentation is much smaller than the segmentation at the international level. U.S. states share the same currency, language, laws, accounting standards, and federal government. The lack of risk sharing intranationally is even more puzzling than the lack of risk sharing internationally.

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A Maximum likelihood estimation of the factor model

The appendix describes the details of the maximum likelihood estimation of the factor model. The factor model can be written in the general form:

$$x_t = Bf_t + \varepsilon_t,\ t = 1, .., T \tag{9}$$

where x_t is a $n \times 1$ vector of data at time t, f_t is a $n \times 1$ vector of factors, ε_t is a $n \times 1$ vector of idiosyncratic shocks, and B is a $n \times k$ matrix of parameters. Both the factors and the idiosyncratic shocks are normally distributed:

$$f_t \rightsquigarrow N(0, I),\ \varepsilon_t \rightsquigarrow N(0, \Phi), \tag{10}$$

where Φ is a diagonal matrix. The model (9) encompasses models (1), (6), and (7). In order to check for the robustness of the results, I use two different approaches to the maximum likelihood problem, the EM algorithm and a Newton-Raphson routine.

The EM algorithm was first applied to factor models by Lehmann and Modest (1985). This is a generalization of their approach to the case in which a set of linear restrictions is applied to the matrix B. The EM algorithm follows the intuition that if the factors were observable all the parameters could be estimated by means of OLS. The algorithm is an iterative procedure that consists of two steps (see also Gelman et al. 1995). For a given value of the parameters obtained at the end of the q^{th} iteration of the algorithm, that is, (B^q, Φ^q), the first step involves taking the expectation (E) of the logarithm of the joint posterior distribution of B, Φ, and f, given the observations $x \equiv (x_1, .., x_T)$, with respect to the conditional distribution of f given (B^q, Φ^q) and x. The second step consists in maximizing (M) the resulting expression with respect to (B, Φ). Each iteration of the algorithm is bound to increase the likelihood, so that convergence to a, possibly local, maximum is guaranteed.
In the case of model (9), the first step results in the expression:

$$E_q[\ln pdf(B, \Phi, f/x)] = -\frac{T}{2}\{\ln|\Phi| + tr\{\Phi^{-1}[S - 2B(\sum_{t=1}^{T} \frac{E_q[f_t]x_t'}{T}) + B(\frac{E_q[f_t f_t']}{T})B']\} \tag{11}$$

where S is the variance-covariance matrix of the observations, and $E_q[.]$ represents the expectation taken with respect to the conditional distribution of f given (B^q, Φ^q) and x. The terms $E_q[f_t]$ and $E_q[f_t f_t']$ can be easily obtained from normal updating.
Since the joint maximization of (11) with respect to (B, Φ) is complicated, I adopt a variant of the EM algorithm, known as ECM, in which the (M) step is split into a number of conditional

maximization (CM). The first CM step consists in maximizing (11) with respect to B, given Φ^q. In order to implement the maximization one needs to deal with the linear restrictions (mostly zero restrictions) imposed on the matrix B. Let us call b the $p \times 1$ vector of unconstrained parameters, and M the $p \times nk$ matrix that maps b into $vec(B')$. Then the first CM step yields:

$$b^{q+1} = [M(\Phi^{q\ -1} \otimes \frac{E_q[f_t f_t']}{T})M']^{-1} M(\Phi^{q\ -1} \otimes \frac{E_q[f_t]x_t'}{T}). \tag{12}$$

The last CM step delivers the estimate of Φ given B^{q+1}:

$$diag(\Phi) = diag(S - 2B^{q+1}\frac{E_q[f_t]x_t'}{T} + B^{q+1}\frac{E_q[f_t f_t']}{T}B^{q+1\prime}).$$

The implementation of the Newton-Raphson routine is done using the Matlab program *csminwel* obtained from Chris Sims. The likelihood function cab be written as:

$$L(B, \Phi/x) = -\frac{T}{2}(\ln|V| - tr(V^{-1}S)), \tag{13}$$

where $V \equiv BB' + \Phi$ is the theoretical covariance matrix. The implementation of the Newton-Raphson routine is greatly enhanced in terms of both speed and precision by the computation of the analytical gradient. The gradient with respect to b is $-TM'vec((V^{-1} - V^{-1}SV^{-1})B)$, and the gradient with respect to the diagonal elements of Φ is $-\frac{T}{2}diag(V^{-1} - V^{-1}SV^{-1})$.

The criteria for algorithm convergence were: i) incremental changes in the log-likelihood had to be less than $1e^{-10}$, and ii) the sum of the square of the gradients had to be less than $1e^{-4}$. While none of the two algorithms guarantees convergence to a global maximum, the algorithms were implemented from different starting points. Also, the use of two algorithms represents an additional check for robustness. The variance-covariance matrix of the parameters is computed as the inverse of the Hessian of the likelihood at the peak. The Hessian is obtained via numerical differentiation of the gradient. The delta method was used to perform tests on non-linear functions of the parameters, like the standard deviations of asymmetric shocks.

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Notes

[1]See Asdrubali et al. (1996), Athanasoulis and van Wincoop (1997a) (1997b), Atkeson and Bayoumi (1993), Bayoumi and Klein (1995), Crucini (1998), Crucini and Hess (1999), Del Negro (1998a), Hess and Shin (1997) (1998), Mélitz and Zúmer (1999), Sørensen and Yosha (1997) (1998), van Wincoop (1995).

[2]See Eichengreen (1990) among several others, and Frenkel and Rose (1997) for a critique of this literature.

[3]A number of papers (e.g. Clark, 1998; Ghosh and Wolf, 1997; Kollmann, 1995; Norrbin and Schlagenhauf, 1988) study the relative importance of regional and sectoral shocks within U.S. states or regions. These studies focus on fluctuations in employment, industrial production, and productivity. This literature is reviewed in Clark and Shin (1999). Carlino and Sill (1998) and Wynne and Koo (1999) analyze co-movements across U.S. regions in per capita income and output, respectively.

[4]In standard factor models identification is obtained by means of the so called canonical restrictions, which have no economic content. The set of restrictions adopted here, based on geographic proximity, may not necessarily be the best one: one can think of grouping different states on the basis of different criteria, such as the productive structure, or the level of income (see Sørensen and Yosha 1997). However, geographic proximity may in some cases be a proxy for some of these features, as geography plays an important role in defining the productive structure of a given area (see Krugman 1991).

[5]As discussed in the remainder of the paper, the de-trending methods used here are first differences and the HP filter. Since under both methods a linear operator is applied to the (log of) the data, it does not matter whether one first de-trends the log of per capita state consumption (output) and the log of per capita U.S. consumption (output) and then takes the difference between the two, or vice versa.

[6]The approach adopted in this paper also differs from the one followed by Stockman (1988), who estimates a similar model using dummy variables. While this model is more complicated than Stockman's in terms of implementation, it has the advantage of being more economical in terms of the number of parameters that need to be estimated. Stockman uses a dummy variable for each factor in each time period: since there are 59 factors and 26 time periods, that would have meant estimating $26 \times 59 = 1508$ parameters instead of 400. More importantly, Stockman's method does not allow for

the same factor to have a different impact on different states, or a different impact on consumption and output in the same state. This would have been a major impediment in addressing questions regarding the relative variability of consumption and output, and the fraction of variability that can be attributed to each factor.

[7]In some of the literature (for example Von Hagen and Hammond 1995) differences in the exposure to the U.S. business cycle are not included in the definition of asymmetric shocks. We chose to include them because if we ignored this component our definition of asymmetric shocks would not be consistent with the definition of perfect risk-sharing used in the literature. For states to be perfectly sharing risk it must be that: i) state or region-specific shocks do not affect their consumption, ii) common shocks affect all states in the same way. The latter requirement suggests that differences in the exposures to U.S. business cycles should be included in the definition of asymmetric shocks.

[8]It is well known that one implication of complete markets when agents' preferences display constant relative risk aversion is the following (see for instance Obstfeld 1994):

$$c_{it} = c_t^{us} + \theta_{it}$$

where c_{it} and c_t^{us} represent the growth rates of consumption in state i and in the aggregate, respectively, and the term θ_{it} represents preference shocks and/or measurement error. Due to the presence of θ_{it} the correlation in consumption growth rates between states i and j may be less than one even under perfect risk sharing (see also Stockman and Tesar 1995).

[9]Kose et al. (1999) and Forni and Reichlin (1998) estimate a dynamic factor model with annual data. Another example of estimation of a dynamic factor model is Gregory et al. (1997).

[10]See Friedenberg and Beemiller (1997).

[11]Regarding the quality of Sales&Marketing Management retail sales data, in Del Negro (1998b) I compare the Census and the Sales&Marketing Management non-durable retail sales data for the nineteen states for which both are available. In particular, I use a bivariate factor model of the form:

$$\begin{aligned} c_{it}^{S\&M} &= c_{it}^{*} + \theta_{it}^{S\&M} \\ c_{it}^{C} &= c_{it}^{*} + \theta_{it}^{C} \end{aligned}$$

where $c_{it}^{S\&M}$ and c_{it}^{C} are the proxies for de-trended consumption of non-durables in state i obtained from Sale&Marketing Management and the Census, respectively, c_{it}^{*} represents the "true" measure of consumption, which is not observed, and $\theta_{it}^{S\&M}$ and θ_{it}^{C} represent the measurement error for each proxy. The comparison between the standard deviation of $\theta_{it}^{S\&M}$ and θ_{it}^{C} reveals that for the majority of states the Census measures are more precise. However, for none of the nineteen states am I able to reject the hypothesis that the two standard deviations are different at the 10% significance level.

[12]The District of Columbia is not included in the analysis precisely for this reason.

[13]The difference between including nineteen or fifty states in the analysis can be appreciated by comparing the results for data sets 1 (HS) and 4 (the output measures and the time period is the same) shown in table 4 and Fig. 2. Using the shorter (1978-1995) versus the longer (1969-1995) time span also makes some difference, as can be seen by estimating the model for data set 3 using the shorter period (the results are not shown for lack of space).

[14]Asdrubali et al. uses total consumption (both private and public) as a measure of consumption. All other data sets use non durable consumption. In order for the comparison between data sets to make sense, when estimating model (6) we replace their measure of consumption with the Sales&Marketing Management measure of non durable consumption. The results are however qualitatively the same when we use their measure of consumption.

[15]For models (6) and (7) the estimated standard deviation (that is, the standard deviation computed using the estimated parameters) and the actual standard deviation do not always coincide. In principle, the maximum likelihood estimates of the parameters ϕ^i (the variances of idiosyncratic shocks) should equalize the actual and the estimated standard deviations. Due to numerical problems, this is not always the case for models (6) and (7), no matter how stringent the convergence criteria for the likelihood and for the gradient are (see appendix). This is not an issue for model (1), or for the consumption data in model (7), suggesting that the problem may arise from the presence of both common and idiosyncratic measurement error. This problem generally affects only one of the two output or consumption data, the most volatile. In essence, this numerical issue implies that the idiosyncratic standard deviation for the most volatile data is either under or overestimated. For the less volatile measure of either consumption or output the actual and the estimated standard deviations roughly coincide, and these are the figures shown in table 5 and figure 3 for the case *with measurement error*. In the case

without measurement error the standard deviation of asymmetric shocks is the same across data sets by construction.

[16]The figures shown in table 6 are the averages across states of the absolute values of the coefficients β_{yi}^{us}, β_{yi}^{r}, et cetera. It is important to note that these figures do not add up to the overall estimated standard deviation of asymmetric shocks, as the latter is not a linear function of the coefficients.

[17]This may be the case if a large idiosyncratic movement in consumption and a small movement in output are coincidental. In fact, for these states the exposure of output on state-specific shocks is small and insignificant.

Tables

Table 1: The data

Data set:	nominal consumption	consumption deflator	nominal output	output deflator
Data set 1 (HS): 19 states, 1978-95				
	retail sales (non durables)	state CPI	gsp	gsp deflator
	source: Census	source: Del Negro	source: BEA	source: BEA
Data set 2 (ASY): 50 states, 1969-95				
	retail sales (total)+ S&L gvmt. consumption	US CPI	gsp	US gdp deflator
	source: Sales&Marketing, U.S. Stat. Abstract	source: BLS	source: BEA	source: BEA
Data set 3: 50 states, 1969-95				
	retail sales (non durables)	state CPI	gsp	state CPI
	source: Sales&Marketing	source: Del Negro	source: BEA	source: Del Negro
Data set 4: 50 states, 1978-95				
	retail sales (non durables)	state CPI	gsp	gsp deflator
	source: Sales&Marketing	source: Del Negro	source: BEA	source: BEA

Note: The frequency is annual for all data. In data set 2, total retail sales for each state are multiplied by the ratio of total U.S. consumption over total U.S. retail sales for the corresponding year.

Table 2: Autocorrelation of relative consumption and relative output

	consumption	output
Data set 1 (HS): 19 states, 1978-95		
growth rates	-0.000952 (0%)	0.166 (21.1%)
HP filter	0.09 (0%)	0.142 (10.5%)
Data set 2 (ASY): 50 states, 1969-95		
growth rates	0.0305 (10 %)	0.263 (40%)
HP filter	0.154 (8%)	0.253 (32%)
Data set 3: 50 states, 1969-95		
growth rates	-0.0665 (10%)	0.21 (24%)
HP filter	0.105 (12%)	0.219 (26%)
Data set 4: 50 states, 1978-95		
growth rates	-0.0413 (8%)	0.184 (20%)
HP filter	0.0992 (4%)	0.157 (10%)

Note: Averages across states. The figures in parenthesis show the percentage of states for which the autocorrelation coefficient is significantly different from zero at the 5% level.

Table 3: Cross correlation of consumption and output

	consumption	output	difference	%
Data set 1 (HS): 19 states, 1978-95				
growth rates	0.302 (0.236)	0.703 (0.186)	-0.401	94.2
HP filter	0.33 (0.25)	0.776 (0.181)	-0.446	94.7
Data set 2 (ASY): 50 states, 1969-95				
growth rates	0.267 (0.245)	0.494 (0.331)	-0.227	79.8
HP filter	0.334 (0.265)	0.557 (0.367)	-0.223	78.7
Data set 3: 50 states, 1969-95				
growth rates	0.314 (0.219)	0.535 (0.337)	-0.221	75.8
HP filter	0.295 (0.243)	0.586 (0.383)	-0.291	78.9
Data set 4: 50 states, 1978-95				
growth rates	0.152 (0.284)	0.509 (0.279)	-0.357	83.9
HP filter	0.131 (0.301)	0.56 (0.302)	-0.428	86.2

Note: The first and second columns show the cross-sectional average (and standard deviation) of the correlations of consumption and output, respectively. The third column shows the difference between the two. The forth column shows the percentage of states for which the correlation in output is larger than the correlation in consumption.

Table 4: Standard deviations of asymmetric shocks - model (1)

		consumption	output	difference	%
Data set 1 (HS): 19 states, 1978-95					
growth rates	- with idiosyncratic component	3.32	1.67	1.64	100 (100)
	- without idiosyncratic component	2.48	1.67	0.802	89 (100)
HP filter	- with idiosyncratic component	2.14	1.02	1.12	100 (100)
	- without idiosyncratic component	1.67	1.02	0.648	79 (100)
Data set 2 (ASY): 50 states, 1969-95					
growth rates	- with idiosyncratic component	3.42	2.69	0.729	86 (88)
	- without idiosyncratic component	1.84	2.69	-0.851	26 (6)
HP filter	- with idiosyncratic component	2.24	1.74	0.502	86 (87)
	- without idiosyncratic component	1.42	1.74	-0.316	44 (37)
Data set 3: 50 states, 1969-95					
growth rates	- with idiosyncratic component	4.19	2.75	1.44	94 (91)
	- without idiosyncratic component	2.22	2.75	-0.523	48 (7)
HP filter	- with idiosyncratic component	2.79	1.79	1	92 (91)
	- without idiosyncratic component	1.86	1.79	729	60 (52)
Data set 4: 50 states, 1978-95					
growth rates	- with idiosyncratic component	4.19	2.23	1.95	94 (98)
	- without idiosyncratic component	2.55	2.23	0.319	58 (50)
HP filter	- with idiosyncratic component	2.76	1.38	1.37	92 (98)
	- without idiosyncratic component	1.84	1.37	0.462	66 (68)

Note: Figures are in %. The first and second columns show the cross-sectional average of the standard deviations of asymmetric shocks in consumption and output, respectively. The third column shows the difference between the two. The forth column shows the percentage of states for which the standard deviation of asymmetric shocks in consumption is larger than the standard deviation of asymmetric shocks in output, considering all states, and considering only those states for which the difference is significantly different from zero at the 5% level (in parenthesis).

Table 5: Standard deviations of asymmetric shocks - models (6) and (7)

		consumption	output	difference	%
Data sets 1(HS) and 2 (ASY): 19 states, 1978-95					
growth rates	- with measurement error	3.2	1.7	1.5	100 (100)
	- without measurement error	2.31	1.52	0.79	79 (75)
HP filter	- with measurement error	2.05	1.03	1.01	95 (100)
	- without measurement error	1.49	0.887	0.602	89 (100)
Data sets 1(HS) and 3: 19 states, 1978-95					
growth rates	- with measurement error	3.19	1.75	1.44	100 (100)
	- without measurement error	2.33	1.55	0.771	79 (75)
HP filter	- with measurement error	2.04	1.05	0.99	95 (100)
	- without measurement error	1.51	0.885	0.623	95 (100)
Data set 2 (ASY) and 4: 50 states, 1978-95					
growth rates	- with measurement error	4.2	2.24	1.96	92 (100)
	- without measurement error	3.23	1.82	1.42	78 (100)
HP filter	- with measurement error	2.79	1.37	1.42	94 (98)
	- without measurement error	2.31	1.09	1.22	88 (100)
Data set 3 and 4: 50 states, 1978-95					
growth rates	- with measurement error	4.19	2.26	1.92	94 (100)
	- without measurement error	3.3	1.82	1.48	78 (100)
HP filter	- with measurement error	2.76	1.4	1.35	92 (98)
	- without measurement error	2.24	1.1	1.14	84 (100)

Note: Figures are in %. The first and second columns show the cross-sectional average of the estimated standard deviations of asymmetric shocks in consumption and output, respectively. The third column shows the difference between the two. The forth column shows the percentage of states for which the estimated standard deviation of asymmetric shocks in consumption is larger than the estimated standard deviation of asymmetric shocks in output, considering all states, and considering only those states for which the difference is significantly different from zero at the 5% level (in parenthesis).

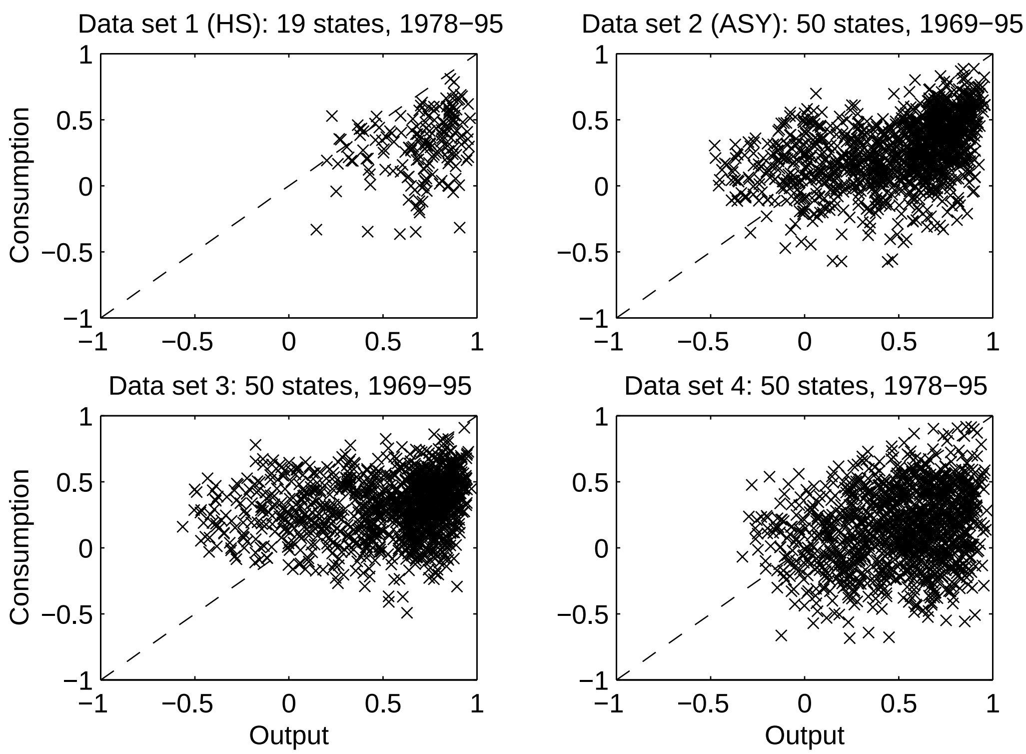
Table 6: The standard deviation of asymmetric shocks due to each factor, cross sectional averages - models (6) and (7)

		U.S.	Region	State	Common	Idios.
Data set 1 (HS) and 2 (ASY): 19 states, 1978-95						
Output 1	-growth rates	0.63 (26)	0.62 (47)	1 (47)	0.33 (0)	0.26 (32)
	-HP filter	0.38 (37)	0.31 (53)	0.6 (42)	0.31 (0)	0.13 (21)
Output 2	-growth rates					0.9 (84)
	-HP filter					0.68 (95)
Consumption 1	-growth rates	1.5 (63)	0.74 (26)	1.1 (11)	0.39 (0)	1.7 (63)
	-HP filter	1.1 (63)	0.5 (37)	0.62 (21)	0.36 (5)	1 (68)
Consumption 2	-growth rates					3 (95)
	-HP filter					1.9 (95)
Data sets 1 (HS) and 3: 19 states, 1978-95						
Output 1	-growth rates	0.61 (32)	0.68 (58)	1 (53)	0.23 (11)	0.43 (42)
	-HP filter	0.34 (32)	0.32 (53)	0.62 (53)	0.3 (0)	0.23 (32)
Output 3	-growth rates					1 (89)
	-HP filter					0.75 (100)
Consumption 1	-growth rates	1.5 (63)	0.69 (26)	1.1 (21)	0.26 (0)	1.8 (68)
	-HP filter	1.1 (74)	0.51 (37)	0.62 (32)	0.33 (0)	1 (68)
Consumption 3	-growth rates					2.9 (95)
	-HP filter					1.9 (95)
Data set 2 (ASY) and 4: 50 states, 1978-95						
Output 4	-growth rates	0.96 (48)	0.88 (40)	0.88 (10)	0.97 (14)	0.38 (32)
	-HP filter	0.39 (32)	0.62 (44)	0.58 (8)	0.63 (16)	0.25 (34)
Output 2	-growth rates					1 (74)
	-HP filter					0.75 (86)
Consumption 2	-growth rates	1.2 (16)	1.5 (34)	2.1 (16)		2.1 (10)
	-HP filter	0.96 (28)	1.1 (40)	1.3 (10)		1.1 (10)
Data set 3 and 4: 50 states, 1969-95						
Output 4	-growth rates	0.96 (44)	0.92 (44)	0.89 (6)	0.92 (4)	0.49 (36)
	-HP filter	0.4 (36)	0.64 (46)	0.6 (6)	0.59 (10)	0.32 (32)
Output 3	-growth rates					1.3 (94)
	-HP filter					0.87 (94)
Consumption 3	-growth rates	1.2 (22)	1.4 (30)	2.2 (14)		1.9 (10)
	-HP filter	0.95 (30)	1.1 (38)	1.3 (12)		1.2 (4)

Note: Figures are in %. The table shows the cross sectional average of the estimated standard deviation of asymmetric shocks due to due to the national (US), regional (Reg.), state specific (St.) factor, and to the common (Common) and idiosyncratic (Idios.) component of measurement error, as well as the percentage of states for which this is significantly different from zero at the 5% level. Specifically, the table shows the cross-sectional averages of the absolute values of the coefficients β_{yi}^{us}, β_{yi}^{r}, etc.

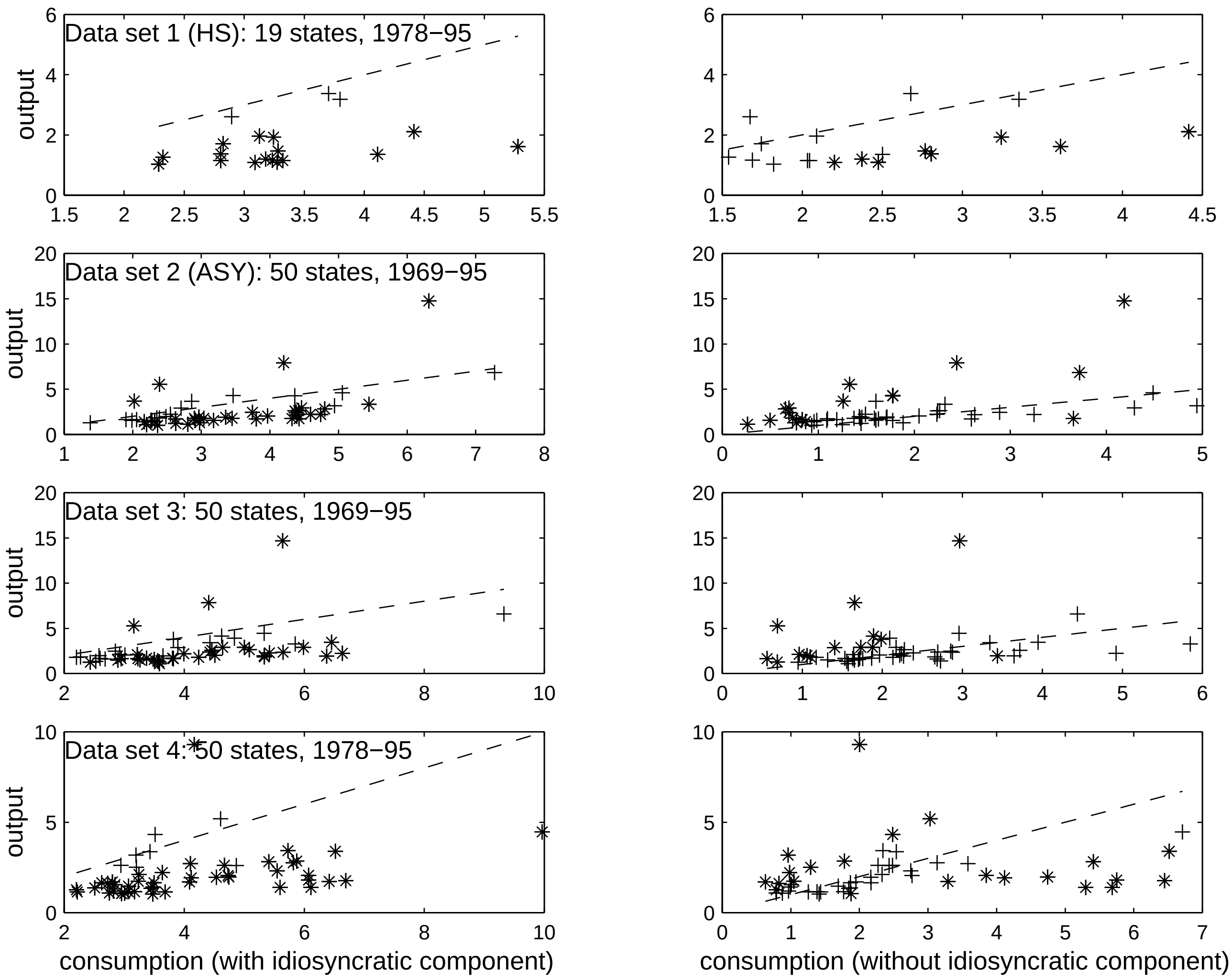
Figures

Figure 1: Cross correlation of output and non-durable consumption across states



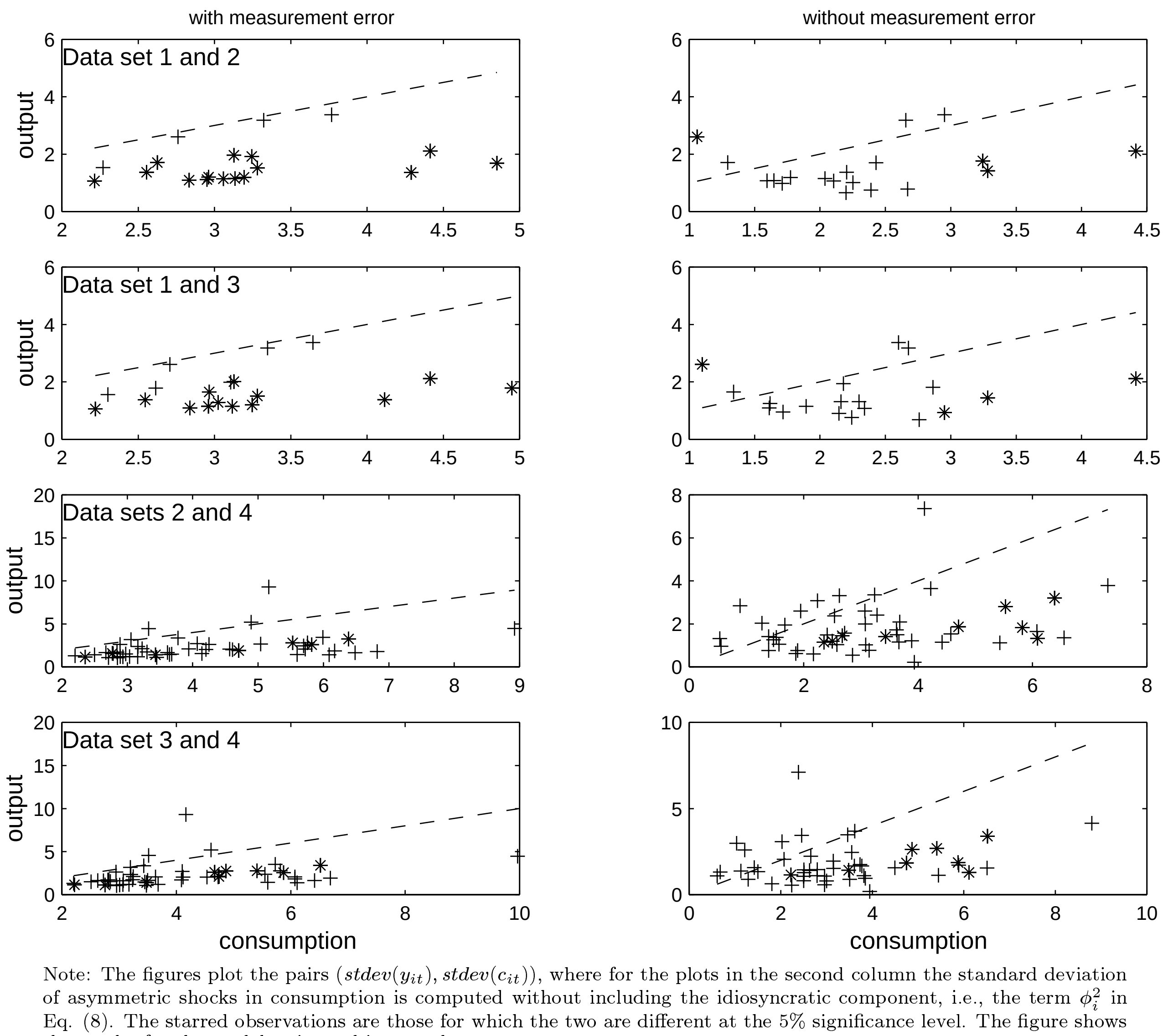
Note: The figures plot the pairs $(Corr(y_i, y_j), Corr(c_i, c_j))$, where y_i and c_i represent de-trended output and consumption in state i respectively. The figure shows the results for the model estimated in growth rates.

Figure 2: Standard deviations of asymmetric shocks to output and non-durable consumption - model (1)



Note: The figures plot the pairs $(stdev(y_{it}), stdev(c_{it}))$, where for the plots in the second column the standard deviation of asymmetric shocks in consumption is computed without including the idiosyncratic component, i.e., the term ϕ_i^2 in Eq. (8). The starred observations are those for which the two are different at the 5% significance level. The figure shows the results for the model estimated in growth rates.

Figure 3: Standard deviations of asymmetric shocks to output and non-durable consumption - models (6) and (7)



Note: The figures plot the pairs $(stdev(y_{it}), stdev(c_{it}))$, where for the plots in the second column the standard deviation of asymmetric shocks in consumption is computed without including the idiosyncratic component, i.e., the term ϕ_i^2 in Eq. (8). The starred observations are those for which the two are different at the 5% significance level. The figure shows the results for the model estimated in growth rates.