Skewed Business Cycles

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Preliminary and Incomplete. Comments Welcome.

Abstract

Using a panel of Compustat firms from 1962 to 2013, we study how the distribution of the growth rates of firm-level variables (sales, profit, and employment) change over the business cycle. In addition to the well-documented countercyclicality in dispersion, we document that the third moment—skewness—is strongly pro cyclical. This happens because the distribution of negative growth rates expands during recessions while the distribution of positive growth rates changes little. In fact, this pattern—of lower tail greatly expanding during recessions—is also the main driver behind the countercyclicality of dispersion. These results are robust to different selection criteria, across firm size categories and across industries. We contrast these results with firm level evidence from a wide sample of countries. Despite the large cross-country heterogeneity, we find a robust positive relation between our measure of skewness and different measures of economic activity.

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1 Introduction

This paper studies the evolution over the business cycle of the higher-order moments of firm-level variables. We find that firms are affected asymmetrically by recessions—the skewness of firm-level shocks declines sharply during recessions. In other words, during economic downturns firms do not only perform worse on average and the dispersion of firm-level outcomes increases, but also, there is a disproportionate number of firms that experience very large negative shocks compared to the mean—more so than would be predicted by a (symmetric) increase in dispersion. As an example, Figure 1 shows the density of firm-level growth rates of sales between 2006Q1 and 2007Q1—just before the Great Recession—superimposed over the density for the same variable between 2007Q2 to 2008Q2—leading up the trough of the recession.

As seen in the figure, the standard deviation of the distribution increases from 0.26 to 0.31.[1] At the same time, a robust measure of skewness—Kelly's skewness—declines from 0.09 to –0.28. One way to explain what the Kelly's skewness measures is as follows. The difference between the 90th and 50th percentiles, denoted P9050, of a distribution is a measure of upper half dispersion, whereas P5010, defined analogously, is a measure of lower half dispersion. Kelly's measure is the difference between these two tail measures, P9050 – P5010, scaled by overall dispersion, P9010. So, a Kelly skewness of 0.09 in 2006–2007 means that P9050 accounts for 55% of overall dispersion (P9010), whereas the lower tail, P5010, accounts for the remaining 45%. The figure of –0.28 in the Great Recession means that the upper tail accounts for only 36% of P9010 and the lower tail accounts for 64%. So, this is a very quick change in the relative sizes of each tail in just one year.

Although, the histogram in Figure 1 pertains to a short period covering just a few years, we show that the same patterns highlighted here are robust across the entire sample we examine, as well as across different firm size categories, different industries, and so on.

To document these facts, we study the time series behavior of the cross sectional moments of the distribution of growth rate of sales in a panel of publicly traded firms. We show that the skewness of the distribution is time varying and strongly correlated with different measures of aggregate economic activity (i.e. per capita GDP growth and

[1] In the same period, the difference between the 75th and 25th percentile of the distribution, another measure of dispersion, increased by 100%.

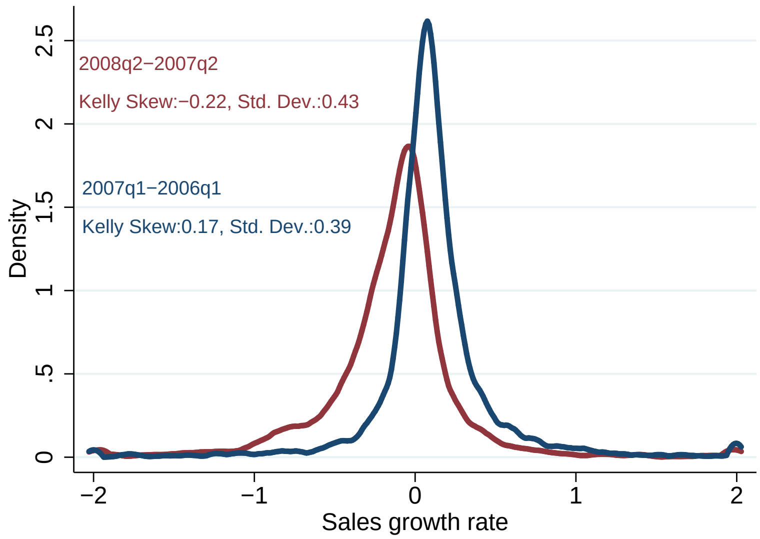


FIGURE 1 – The histogram for each time period is constructed using the arc-percent change between quarter t and $t+4$. The arc-percent change is defined as $g_{i,t} = 2\left(x_{i,t+4} - x_{i,t}\right) / \left(x_{i,t+4} + x_{i,t}\right)$.

the unemployment rate). Additionally, we find that most of the increase of the dispersion observed during recessions comes from the lower part of the distribution. We find similar results when we consider the time series of the growth rates of gross profits, inventories, and annual employment growth.

Establish a clear difference between symmetric and asymmetric changes in dispersion is important for the analysis of individuals and firms responses to business cycle fluctuations. A symmetric increase in dispersion implies an expansion of the left and the right tail of the distribution. In such case, the proportion of firms observing, for instance, a drop in sale 20% below the mean, has to be similar to the proportion of firms observing an increase of 20% above the mean, which in principle, might give to some firms more incentives to invest more during recessions. However, if is only the left tail that expands during recession – a asymmetric increase in dispersion – there is only an increase in the downside risk and therefore the proportion of firms observing growth rate below the mean does not need to be equal to the proportion above the mean.

We also study the cross sectional distribution of the growth rate of sales in a wide sample of European and Asian countries using three additional data sources, Compustat Global, Osiris, and Orbis. Despite the large differences between data sets and countries, we find a robust positive relation between our measure of skewness and different measures of economic activity like the growth rate of GDP per capita, the growth rate of aggregate investment, and the growth rate of aggregate consumption.

This paper is related to several strands of literature. First, there is a recent body of research that stresses the importance of rare disasters—presumably arising from an asymmetric distribution. Barro (2006) argues that low probability events can have substantial implications for asset pricing, while Gourio (2012) extends the standard DSGE model to include probability a small risk of a large negative shock. He finds that an increase in the probability of a disaster induces a contraction in output, employment, and especially, investment. Ruge-Murcia (2012) finds that the U.S. data reject the hypothesis that productivity shocks are normally distributed in favor of an Skew Normal distribution. He also finds that negatively skewed productivity shocks can generate asymmetric business cycles. Our paper provides evidence that the distribution of firm-level shocks is asymmetric and its skewness decreases during recessions, which in turn implies an increase in the probability that firm, or a large number of them, observes a very large negative shock.

Second, the time-varying skewness of firm level shocks implies an additional source of risk, and hence, our paper relates directly to the study of the effects of uncertainty on firms decisions. Bloom (2009), Bloom *et al.* (2011), and Bachmann and Bayer (2014), among others, show that an increase in the uncertainty of firms shocks can lead to a recession. In the type of models that these authors study, an uncertainty shock makes firms less willing to invest or hire because the irreversible cost induced by these decisions. Arellano *et al.* (2012) finds that an increase in uncertainty can lead to a reduction in economic activity in a model where firms are financially constrained. Gilchrist *et al.* (2014) evaluates quantitatively which of these channels, the wait-and-see behavior generated by the adjustment costs of capital and labor, or financial frictions, is more important to account for the empirical evidence. They find that both types of frictions are relevant. The effects on uncertainty also have an impact in other firm-level decisions, like price changes. Vavra (2013) studies a model in which price-setting firms face first and second moment shocks. He finds that such model is able account for two empirical facts: i) the cross-sectional standard deviation of the distribution of price changes is counter cyclical and ii) the standard deviation of price changes correlates strongly with the frequency of price adjustment in the economy. His model predicts that periods of high volatility lead to high price flexibility diminishing the response of aggregate output to nominal stimulus. Our paper adds to this literature suggesting a new source of risk which, in principle, could generate larger effects than those found so far in the literature.

Finally, there is a growing literature that analyzes the cyclical behavior of skewness in different contexts. For instance, Guvenen *et al.* (2014) studies the characteristics of individual level income risk. They find that idiosyncratic shocks do not show any countercyclical variation in dispersion but exhibit strongly procyclical skewness. That is, during recessions the upper tail of the earnings growth rates distribution collapses, while the left tail becomes large, implying a greater probability of observing large negative shocks. We find similar results to theirs, in our case, for firm-level shocks. Ilut *et al.* (2014) studies the asymmetric response of firms to news. Their analysis predict that the distribution of growth rates of employment should be negative skewed which is confirmed by the Census data. We find similar results, however, our focus is the variability of the skewness of the distribution and how it moves during the business cycle.

2 Data

2.1 Sample Selection

The main data source is S&P's Compustat database, from which we obtain data on firm-level quarterly sales (SALEQ), cost of goods sold (COGSQ), and firm-level annual employment (EMP) from 1962Q1 to 2013Q4. Since Compustat registers the value of the net sales, we drop all the firm-quarter observations with negative sales and the firm-year observations with zero or negative employment. The main sample considers firms of Compustat with more than 25 years of data (100 quarters not necessarily continuous). In addition, we consider two other samples for robustness analysis. The first of these samples includes all firms in the Compustat database; the second includes firms with more than 10 year (40 quarters) of data. Table I shows the number of firms and observations for each of these samples. Our baseline measure of growth is the arc-percent change between quarters that are one year apart (t and $t+4$):

$$g_{i,t} = 2\frac{x_{i,t+4} - x_{i,t}}{x_{i,t+4} + x_{i,t}}.$$

This measure has been popularized in the firm dynamics literature by Davis and Haltiwanger (1992). An important advantage of this measure is that while it is similar to a percentage change measure, it allows for entry/exit by including both time t and $t+4$ measure in the denominator, one of which is allowed to be zero.

Table I – Quarterly Sample Characteristics

	All Firms	Exists >10 yrs	Exists >25 yrs
Number of Firms	25,721	9,942	2,322
Obs. (Firms/Quarter)	1,064,714	793,686	323,104
Firms per Quarter (Average)	5,114	3,812	1,552
Mean of Δ(Sales)	0.094	0.085	0.076
Std of Δ(Sales)	0.402	0.355	0.271
Skew of Δ(Sales)	–0.032	–0.120	–0.296
Kurt of Δ(Sales)	9.124	10.607	13.239

In what follows, we measure the cross-sectional dispersion using two statistics: (i) the inter quartile range, IQR (i.e., the difference between the 75th and the 25th percentiles of the sales growth rate distribution) and (ii) the difference between the 90th and 10th percentiles, denoted by $P9010$. In addition, we use the difference between the 90th and 50th percentiles, denoted by $P9050$, and the difference between the 50th and 10th, denoted by $P5010$, as measures of dispersion in the upper and lower parts of the distribution. Our preferred measure of skewness is Kelly's measure and is defined as

$$KSK_t = \frac{P90 - P50}{P90 - P10} - \frac{P50 - P10}{P90 - P10}.$$

Relative to the third standardized moment (which is another measure of skewness), this measure has the advantage to be robust to potential outliers. We also present results on the kurtosis of the distribution which is measured using the coefficient of kurtosis: $\mathbb{E}(x^4)/\sigma_x^4$ for a zero mean random variable x.

3 Microeconomic Skewness

In this section, we show that the skewness of the the distribution of firm level shocks becomes more negative during recessions. We focus on the sample of firms that are present in the sample for more than 25 years so as to ensure that we are tracking a relatively stable sample over time. That said, the main findings are robust to changes in the sample selection criteria, as we show later. Figure 2 shows a time series plot of the skewness of the cross sectional distribution of sales growth. The shaded areas indicate NBER recession dates.

The first point to note is that skewness displays significant variation over time. This is important because if recessions are periods characterized mostly by a decrease in the overall economy activity (first moment shocks) and by an increase in the dispersion of firm-level outcomes (second moment shocks), the other moments of the distribution would be irrelevant and the skewness should bounce around a constant number, presumably, zero. This is clearly not the case. A second point to note is that the movements in skewness are synchronized with the business cycle, showing strong procyclical variation, staying mostly positive during expansions and declining sharply during recessions.

To get a sense of the magnitude of these changes, consider the Great Recession. Immediately before the recession, sales growth displayed a positive skewness. Kelly's measure was 0.10, implying that the upper tail, $P9050$, made up 55% of the overall $P9010$ dispersion, leaving 45% gap for $P5010$. With the onset of the recession, not only average sales dived, which is to expected, but also skewness swung strongly negative. Kelly's measure was –0.28 in 2009, implying that $P5010$ made up 64% of overall sales growth distribution, leaving only 36% for P90-50. This represents a large swing in the relative sizes of the two tails in the span of a few quarters.

Remarkably, the Great Recession is not an outlier and in fact looks typical for the changes in skewness. The 2000-2001 recession displayed an even larger swing in skewness (from a Kelly measure of 0.20 down to –0.30) and the recessions of 1970, 1973, and 1982 displayed swings of similar magnitudes to the Great Recession. Therefore, this first look at the data suggests that the strong procyclicality of skewness is an integral part of a firm's business cycle experience.

We next turn to the second moment, shown in Figure 3. The dispersion of sales growth is countercyclical, a result well known in the literature (see, e.g., Bloom (2009) and the subsequent literature). However, it is useful to ask if the rise in dispersion happens through a symmetric expansion of the firm sales growth distribution, or is driven by one tail more than the other. In light of the results on skewness just discussed, we might strongly suspect the latter to be the case.

To take a closer look, we plot $P9050$ (dashed line) and $P5010$ (solid line) individually in Figure 4. The main takeaway from this graph is that recessions are not characterized by an overall increase in dispersion but mostly by a large increase in the dispersion in the lower part of the distribution with little change in the dispersion of the upper half. In other words, most of the increase in the volatility that happens during periods of low economic activity is coming from a disproportionate number of firms that are observing very negative shocks compared to the mean.

FIGURE 2 – Cross Sectional Skewness of Sales Growth

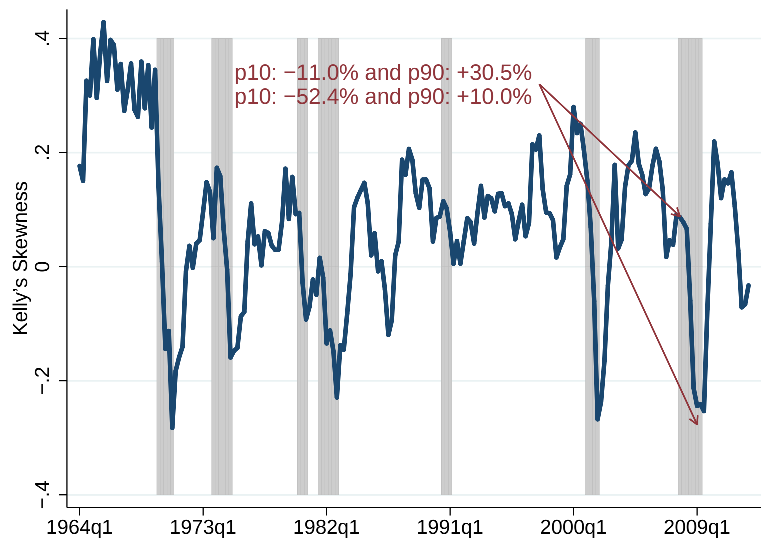


Table II evaluates more directly the relation between different moments of the distribution of sales growth rates and recessions. In the first two columns we regress our measures of dispersion, IQR and $P9010$, on a recession dummy—equal to 1 if the corresponding calendar quarter is part of a recession ($Recess.$). We find that dispersion is counter-cyclical. The third column shows that Kelly's skewness declines during a recession by 0.17 (a coefficient that is highly significant with a t-stat of –8.25). The next two columns (4 and 5) show that P9050 changes very little in recessions, whereas P5010 increases strongly, from an expansion value of 0.19 up to 0.26 in recessions. [2] Finally, column 6 shows the coefficient of kurtosis declines from 13.6 down to 11.6 in recessions, a difference that is also statistically highly significant.[3]

Recall that these results are based on a sample of firms that continue to operate for at least 25 years, which may raise concerns about survivorship bias. Therefore, to investigate the robustness of these results to sample selection, we consider the two alternative samples of firms. In the first sample (denoted the Y10-sample) we restrict the panel of Compustat firms to those with 10 or more years of data (40 quarters or more). A second sample relaxes sample inclusion criteria even further by including all

[2]These results are robust to alternative measures of upper and lower tails, such as the the 75th-50th and 50th-25th differentials, and for different definitions of growth rates.

[3]We do not find any significant relation between the indicator of recessions and the standard deviation of the distribution or the coefficient of skewness. In the first case we find a coefficient of .012 and in the second of -.116. None of them is significant at the 10%.

FIGURE 3 – Cross Sectional Dispersion of Sales Growth

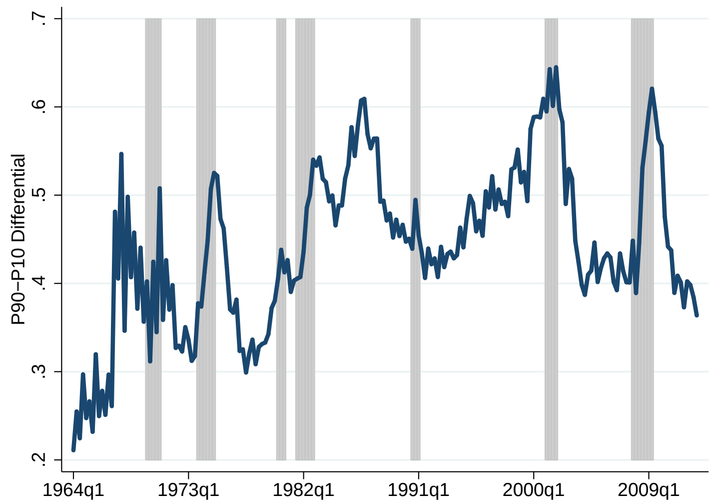


TABLE II – Cross sectional moments during recessions

	(1) IQR	(2) $P9010$	(3) KSK	(4) $P9050$	(5) $P5010$	(6) KUR
Recess	0.0356***	0.0706***	-0.170***	-0.00472	0.0709***	-1.987**
	(4.75)	(3.61)	(-8.25)	(-0.50)	(6.37)	(-3.27)
cons	0.169***	0.423***	0.0957***	0.230***	0.190***	13.61***
	(52.99)	(50.75)	(10.91)	(57.10)	(40.18)	(52.63)
R^2	0.100	0.0605	0.252	0.00123	0.167	0.0504
N. of Obs.	204	204	204	204	204	204

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Compustat firms (Y1 sample).

Tables III and IV present the same analysis of Table II for these two samples. Two points are worth noting. First, the relation between the measures of dispersion, IQR and $P9010$, and the recession dummy becomes slightly weaker as we broaden the sample to include less stable firms. This means that selection can be relevant for the relation between dispersion and recessions, although the effect seems quantitatively small. Second, the relation of the skewness (KSK) and the lower end dispersion, $P5010$, with the recession dummy are still significant in each of the samples.

Is there any systematic relation between the moments of the distribution of sales growth and aggregate measures of economic activity like GDP growth or unemployment?

Figure 4 – Low and High dispersion of Sales Growth Rates

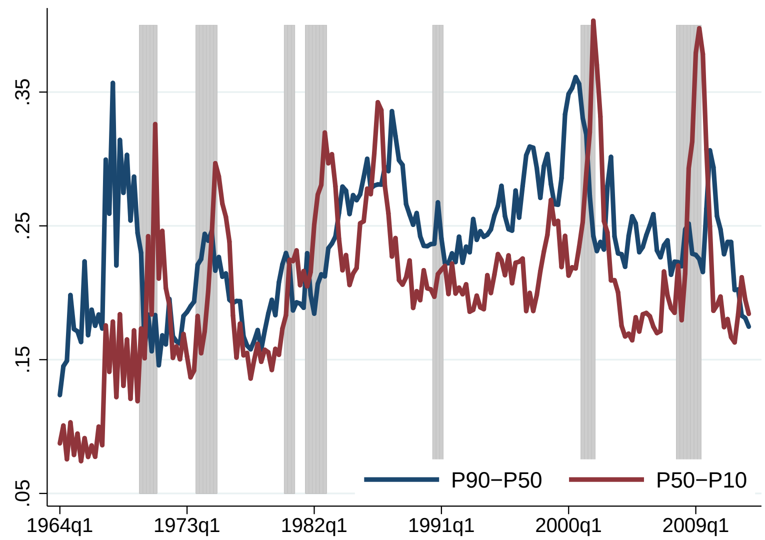


Table III – Moments of the Distribution during Recessions, Y10 Sample

	(1) IQR	(2) $P9010$	(3) KSK	(4) $P9050$	(5) $P5010$	(6) KUR
Recess	0.026*	0.042	–0.132***	–0.017	0.059***	–1.177*
	(2.41)	(1.31)	(–7.24)	(–1.03)	(3.69)	(–2.17)
cons	0.211***	0.544***	0.0979***	0.297***	0.245***	11.24***
	(45.58)	(40.00)	(12.61)	(40.99)	(36.20)	(48.76)
R^2	0.028	0.008	0.206	0.005	0.063	0.023
N. of Obs.	204	204	204	204	204	204

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table IV – Moments of the Distribution during Recessions, Y1 Sample (All Firms)

	(1) IQR	(2) $P9010$	(3) KSK	(4) $P9050$	(5) $P5010$	(6) KUR
Recess	0.0251	0.0436	–0.136***	–0.0177	0.0622**	–0.591
	(1.86)	(1.07)	(–7.26)	(–0.78)	(3.24)	(–1.33)
cons	0.233***	0.619***	0.117***	0.343***	0.274***	9.685***
	(40.42)	(35.74)	(14.65)	(35.39)	(33.51)	(51.02)
R^2	0.0168	0.00565	0.207	0.00299	0.0495	0.00863
N. of Obs.	204	204	204	204	204	204

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

To answer this question Table V shows the results from a regression of some moments of the sales growth distribution on the growth rate of GDP per capita. Here we find that the skewness of the distribution of sales growth co moves with the economic activity. The last row of Table V shows the effect a change of one standard deviation of GDP growth on the level of the corresponding cross sectional moment. For instance, in the case of the Kelly skewness, a decrease in the GDP growth of one standard deviation reduces the skewness in 0.058.[4]

For completeness, Table VI shows the relation between the same moments and the unemployment rate. In this case we also find a strong relation between the unemployment rate and the skewness and between the unemployment rate and the dispersion below the median. The last line shows how much each moments changes when the unemployment rate varies in one standard deviation.[5]

Table V – Business Cycle Variation in Cross-Sectional Moments - GDP Growth

	(1) IQR	(2) $P9010$	(3) KSK	(4) $P9050$	(5) $P5010$	(6) KUR
$\beta_{g_{GDP}}$	–0.457***	–1.047**	2.541***	–0.0293	–0.953***	3.110
	(-3.55)	(-3.16)	(6.91)	(–0.18)	(–5.09)	(0.30)
cons	0.184***	0.456***	0.0204	0.230***	0.219***	13.17***
	(46.13)	(44.39)	(1.78)	(46.87)	(37.73)	(40.54)
R^2	0.059	0.047	0.191	0.001	0.114	0.001
N. of Obs.	204	204	204	204	204	204
$\beta_{g_{GDP}} \times \sigma_{g_{GDP}}$	–0.010	–0.024	0.058	–0.000	–0.021	0.071

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table VI – Business Cycle Variation in Cross-Sectional Moments - Unemployment

	(1) IQR	(2) $P9010$	(3) KSK	(4) $P9050$	(5) $P5010$	(6) KUR
β_u	0.368*	0.424	–1.817**	0.0466	0.592*	58.06***
	(2.04)	(0.88)	(-3.26)	(0.21)	(2.15)	(4.19)
cons	0.152***	0.410***	0.190***	0.227***	0.163***	9.685***
	(13.43)	(13.54)	(5.40)	(16.15)	(9.41)	(11.10)
R^2	0.0202	0.00383	0.0499	0.000217	0.0223	0.0800
N. of Obs.	204	204	204	204	204	204
$\beta_u \times \sigma_u$	.006	.006	-.029	0.000	0.009	.952

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[4]In the sample period, the standard deviation of the growth of GDP per capita was 2.3 percent.

[5]In the sample period, the standard deviation of unemployment was 1.6 percent.

The previous results has been drawn directly from firm-level outcomes without conditioning on any observable characteristics of the firms. As we show in subsequent sections, firms with different sizes differ substantially in terms of the higher order moments of sales growth. Additionally, firm's sales growth rate can be affected by their age, the industry that they belong, or the aggregate economy conditions. Here we attempt to control for such factors. In particular, we study the cross sectional distribution of the residuals of the following regression, $\widehat{\epsilon}_{it}$,

$$g_{it} = \rho g_{it-1} + X_{it}\beta + \epsilon_{it},$$

in which g_{it} is the growth rate of sales and X_{it} is a set of controls such as age and industry dummies, firm size (employment) and aggregate economic conditions (growth rate of GDP per capita). In this case we use the complete sample of Compustat/CRSP firms and we estimate the parameters using OLS with robust standard errors. Here we are not interested in the estimates of the regression but in the properties of the residuals, that, loosely speaking, can be interpreted as the part of the growth rate of sales that can not be predicted from firm - level observables. Therefore, we take the panel of $\widehat{\epsilon}_{it}$ and we calculate the same set of cross sectional moments discussed above. For the purpose of this paper, the most relevant is our measure of skewness, which is displayed in figure 5. In the graph, the red line is the growth rate of GDP per capita. First notice that, even when controlling for firms and industry observables, the cross sectional Kelly skewness remains highly pro cyclical although, not surprisingly, the relation is smaller in magnitude than the one calculated using the growth rate of sales directly. Second, the time series shows larger swings than the skewess calculated using the growth rate of sales directly – compare this with figure 2. Third, the larger drop in skewness in the sample happened during the Great Recession: the Kelly's skewness went from a positive 0.15 to a negative -.40, which is a almost a four times decline. In the same period, the dispersion of the cross sectional residuals, measured by the 90th to 10th percentile differential, increased around 60%.

FIGURE 5 – Kelly skewness of Residuals

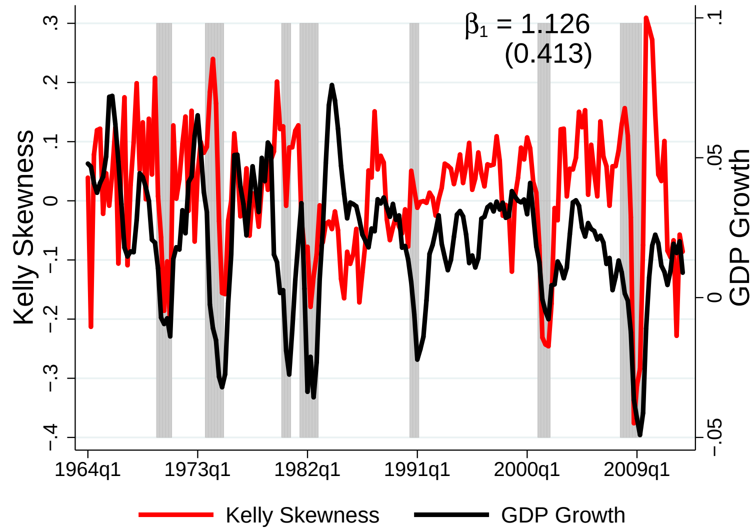


TABLE VII – Distribution of Observations (firm-quarter) Per Categories

Sector	Observations	%
Extraction	13,296	4.12
Utilities	40,036	12.39
Construction	5,550	1.72
Manufacturing	153,351	47.46
Trade	28,632	8.86
Services	80,898	25.04
No classified	1,341	0.42
Total	323,104	100.00

4 Robustness

Skewness in different sectors

The results presented in previous section are not driven by any sector in particular. To see this, here we split the sample of firms with more than 25 years of data in 6 broad categories based on the NAIC identification reported in Compustat. The Table VII shows the number of firms-quarter observations in each of the sectors.

Then, for each of these categories we do the same calculations as in the base sample. The solid line in the Figure 6 shows the results. We also plot the series of the skewness using all the firms in the sample with more than 25 years. A comparison between the

Table VIII – Regressions of Skewness on Recession Dummy, by Sector

	(1) Manuf.	(2) Utilities	(3) Trade	(4) Services	(5) Extraction	(6) Construction
Recess	–0.126***	–0.0602	–0.192***	–0.131***	–0.0391	–0.0376
	(–6.50)	(–1.87)	(–5.34)	(–5.43)	(–0.98)	(–0.96)
cons	0.0521***	0.0508***	0.109***	0.113***	0.0534**	–0.00785
	(6.33)	(3.70)	(7.12)	(10.99)	(3.14)	(–0.47)
R^2	0.173	0.0170	0.124	0.127	0.00472	0.00459
N. Obs.	204	204	204	204	204	204

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

solid and the dashed line shows that the evolution of skewness in each sector is not very different to the what we observe in the sample of firms with 25 years or more, especially in Manufacturing, Trade and Services. This suggests that, in this sample, the procyclicality of skewness is an economy wide phenomenon. Something similar can be observed in the case of the dispersion as is shown in Figure 7 in which the solid line is the difference between the 90th and the 10th percentiles in each sector, and in the case of the coefficient of kurtosis, as is shown in Figure 8.

To complete the analysis, Table VIII shows a set of regressions where the dependent variable is the measure of skewness in each of the sectors and the independent variable is the dummy of recessions. In every sector the partial correlation between the skewness of the distribution of sales growth and the dummy of recessions is negative. Also, we find that the skewness declines more strongly in Trade, Services and Manufacturing while for the rest of the sectors the partial correlation is not statistically significant.

Weighting by the size of the firms

Are the results shown previously driven by a small group of firms that are very volatile and suffer more during recessions? To address this question we calculate a weighted measure of the skewness using, as weights, the employment share of a particular firm over the total employment reported by Compustat.[6] To create the weighted measure of growth rate of sales, we proceed as follows. For each firm i in quarter t of a year k we create a weighted measure of sales as $\tilde{s}_{it} = s_{it} \times \left(Emp_{ik} / \left(\sum_{i=1}^{N_k} Emp_{ik} \right) \right)$ in which Emp_{ik} is the reported value of employment in Compustat for firm i in year k and N_k is the total number of firms in the year k. Then, we calculate the growth rate of $\tilde{s}_{it}$ as

[6] The results are similar when one uses sales or total assets to construct the weights.

FIGURE 6 – Skewness in Different Sectors. The solid line is the cross sectional skewness of the distribution of growth rate of sales in each category. The dashed line is the skewness calculated using the base line sample.

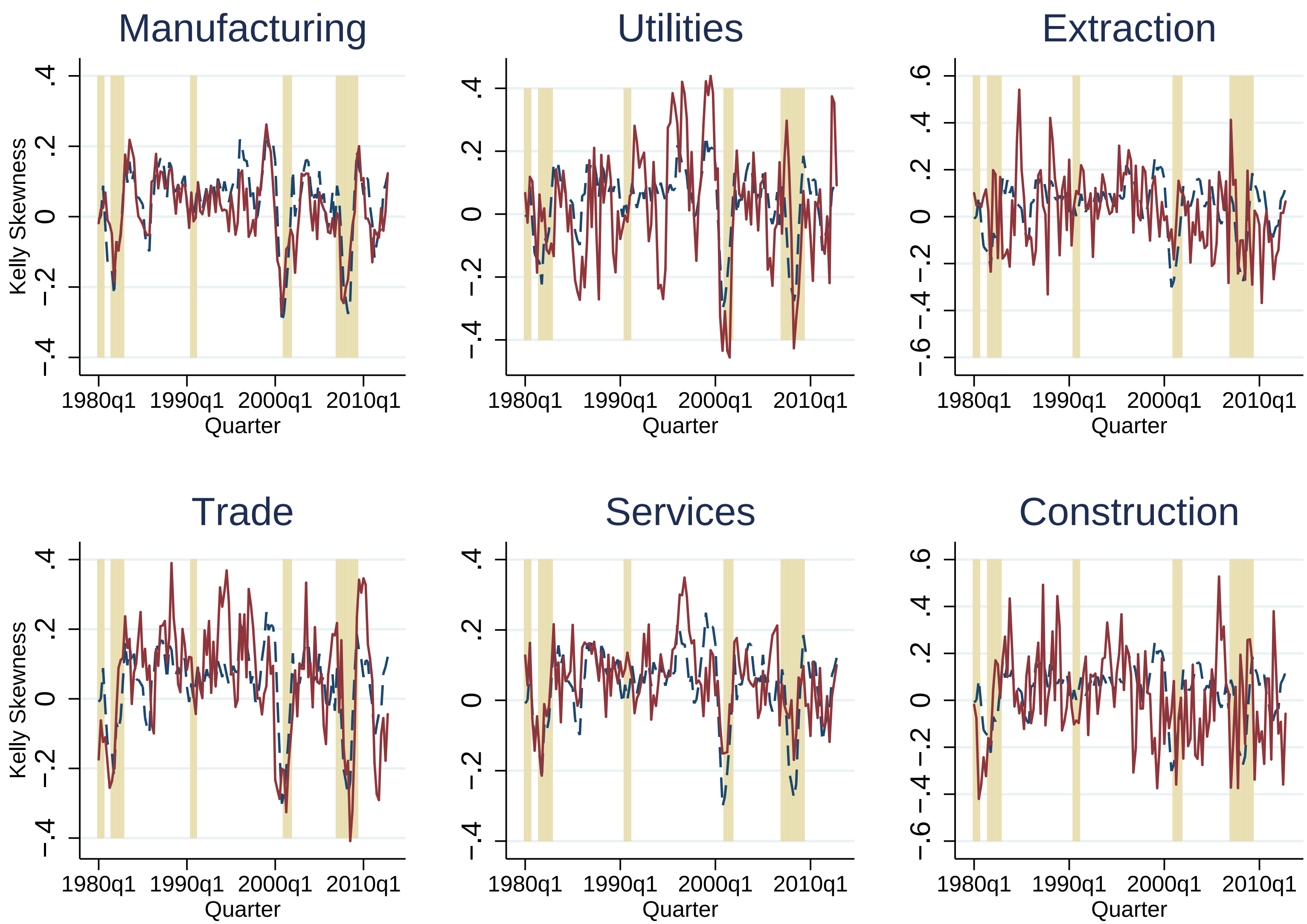


FIGURE 7 – Dispersion in Different Sectors. The solid line is the cross sectional 90th to 10th percentile differential of the distribution of firms in each category. The dashed line is the 90th to 10th differential calculated using the base line sample.

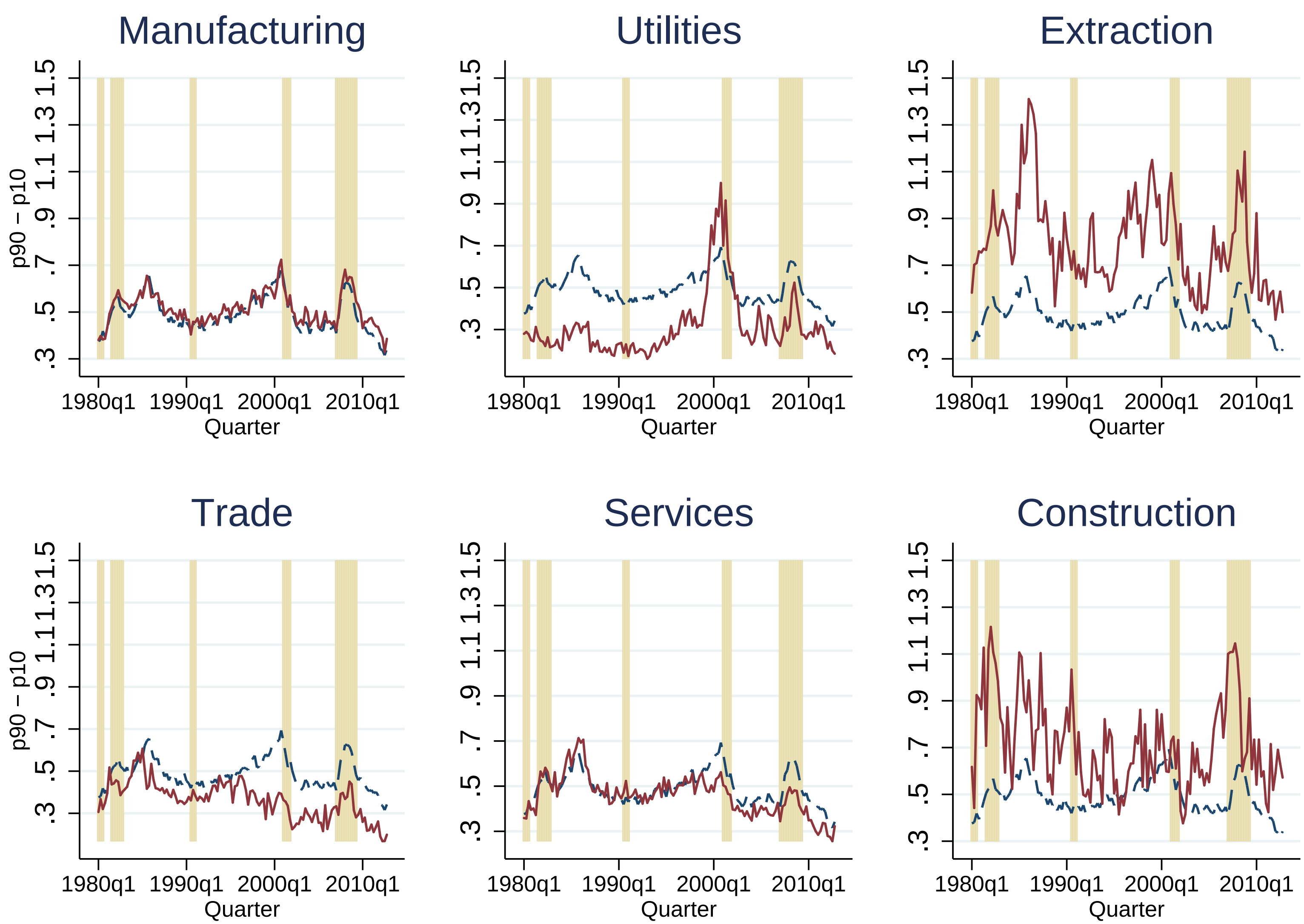


FIGURE 8 – Kurtosis in Different Sectors. The solid line is the cross sectional kurtosis of the distribution of growth rate of sales in each category. The dashed line is the kurtosis calculated using the base line sample.

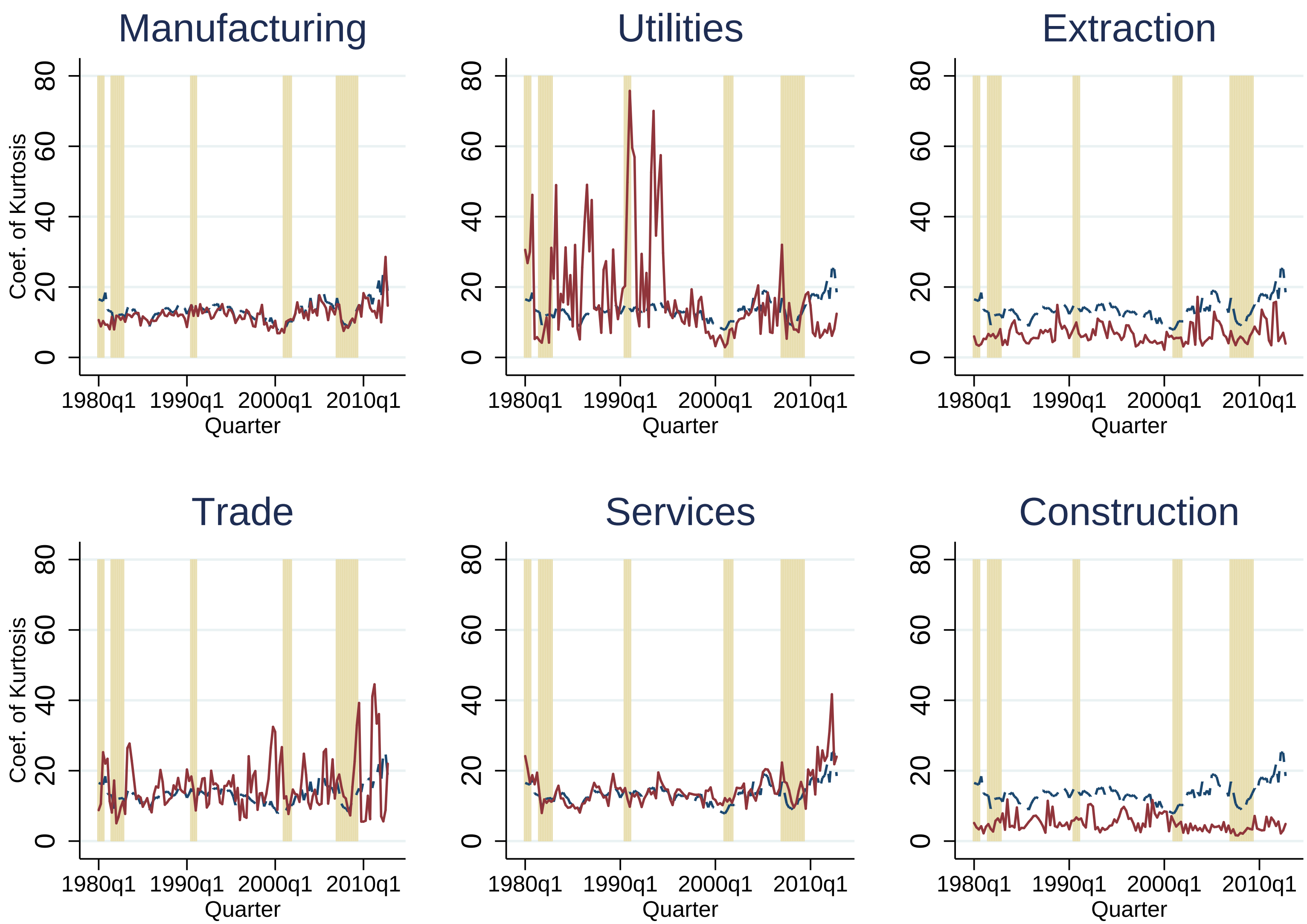


Figure 9 – Weighted and Unweighted Measures of cross sectional Skewness

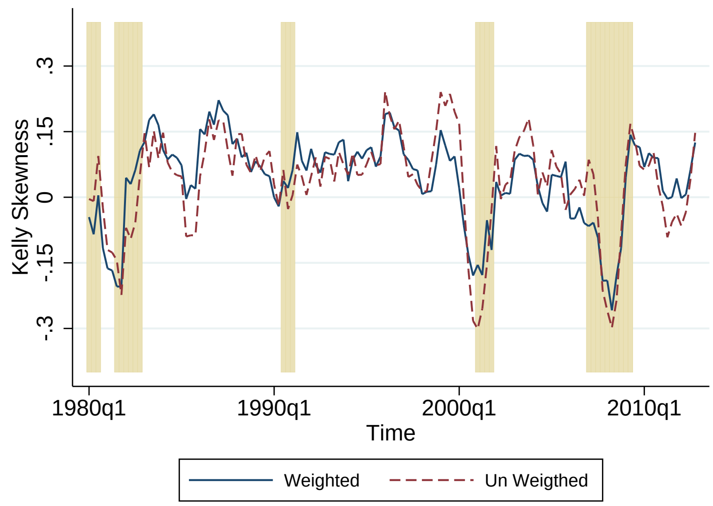
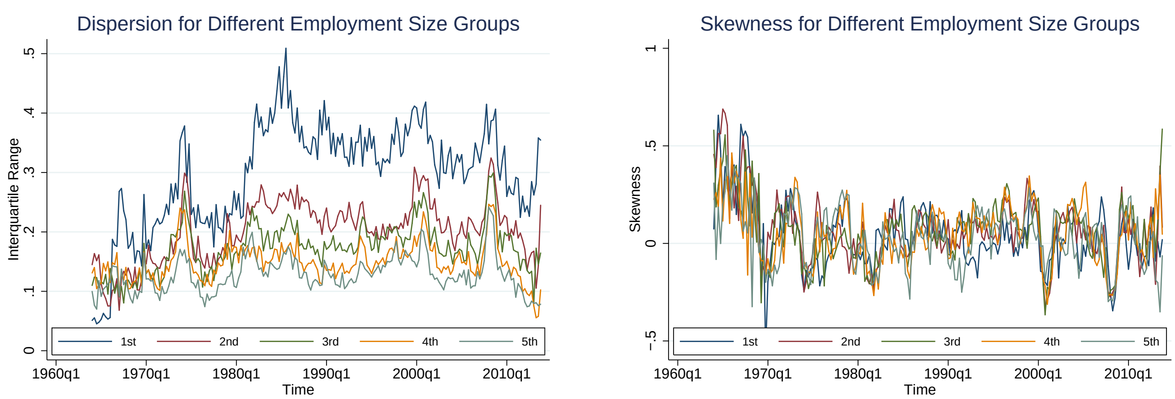
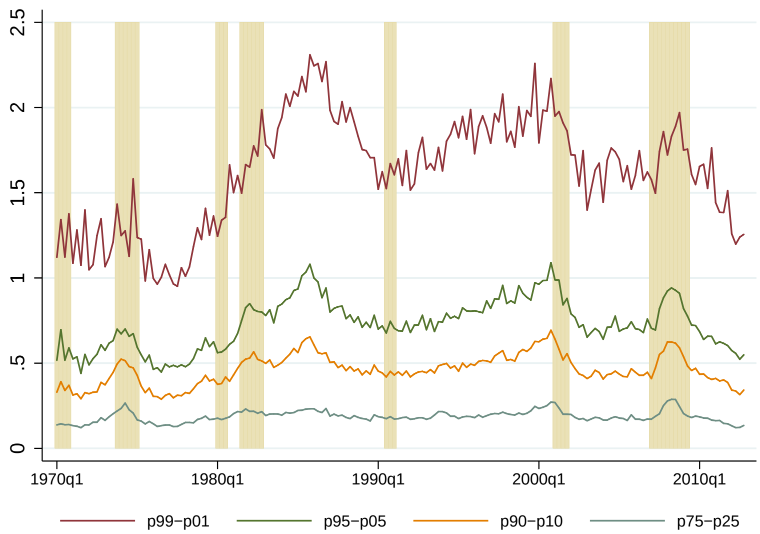


Figure 10 – Dispersion and Skewness for different size-firms groups



the arc-percent change between quarters t and $t+4$. Figure 9 shows the results for the sample of firms with 25 years or more of data. In the case of the weighted measure (solid line) the procyclicality of the skewness is somewhat weaker but still consistent with the main observations. Additionally, we calculate a time series of the interquartile range and the skewness for five different quintiles of the employment distribution. The results are shown in Figure 10. In the left panel one can see that dispersion is higher in the group of smaller firms, while skewness does not varies too much between groups.

FIGURE 11 – Dispersion for Different Percentiles



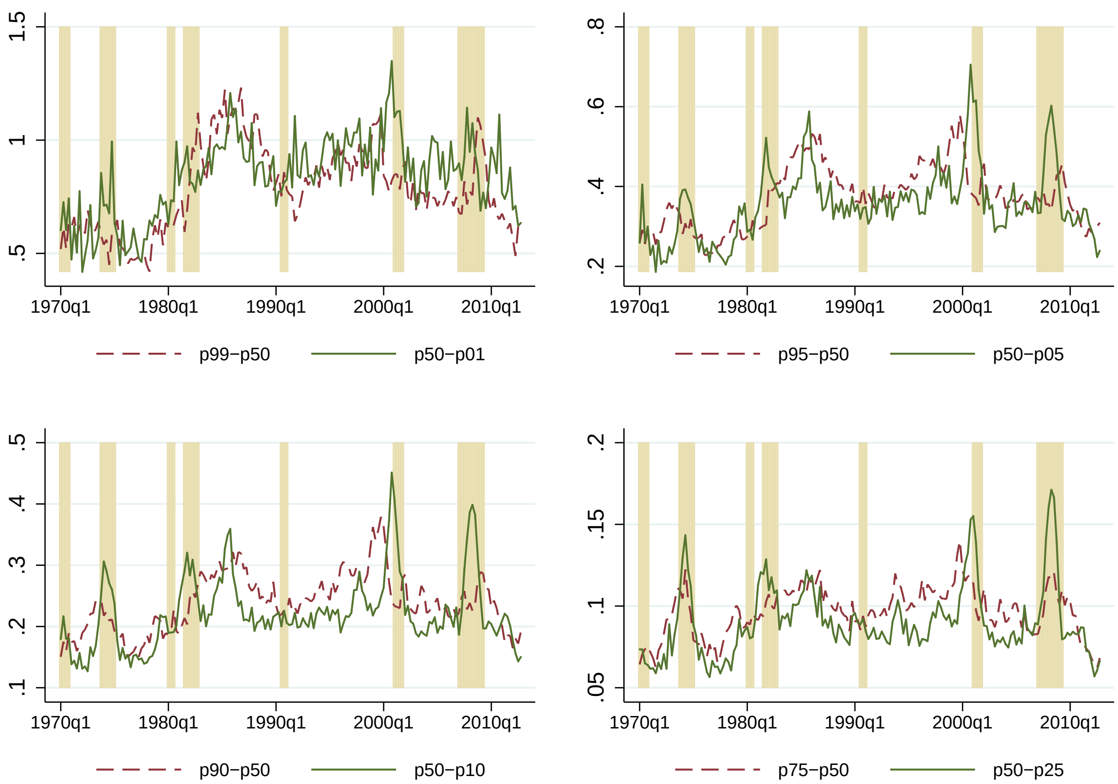
Other Percentiles of the Distribution

Figure 11 shows the time series of dispersion using different percentiles in the distribution. As expected, we find an increase in dispersion during recessions. What is relevant here is that the increase in dispersion is asymmetrical: the difference between the 99th and the 1st percentile, $P99 - P01$, increases more during recessions than the $P90 - P10$ which, in tun, increases more than the $P75 - P25$. Further, the increase in the variability comes mostly from lower part of the distribution as is shown in 12. Here, each plot displays the dispersion above and below the median of the distribution (compare this with Figure 4) for different percentiles. Overall, the figure shows the same results discussed in previous sections: during recessions it is the dispersion in the lower part of the distribution that increases the most.

Gross Profits and Employment growth

The variation observed in the skewness is not only a feature of the distribution of quarterly growth rate of sales but is also observed in other series, like gross profits and employment, and in annual growth rates. First, we consider the data on firm-level gross profits. The gross profit is calculated as the difference between the sales and the cost of production of sold goods. Both series come from Compustat. Figure 13 shows that the evolution of the cross sectional skewness of the growth rate of gross profits and of the growth rate of sales are very similar. This also happens at sectoral level as is

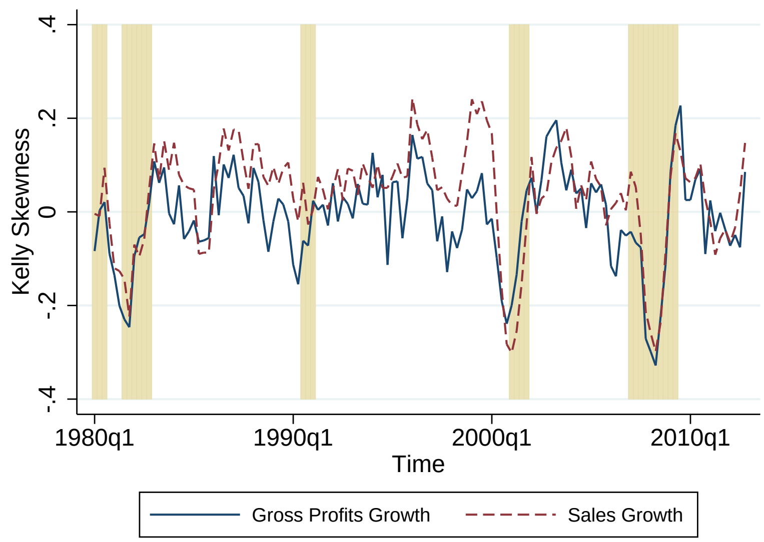
Figure 12 – Upper and Lower Dispersion for Different Percentiles



shown in Figure 26. In the graph, the solid line is the time series of the cross sectional distribution of growth rates of gross profits in each sector, while the dash line is the skewness calculated over the base-line sample.

The cross sectional distribution of growth rate of employment shows similar patters as well, that is, during recessions skewness drops sharply and the dispersion increases mostly in the lower ends of the distribution (Ilut *et al.* (2014) show similar results using Census data). This is true at aggregate level, as well as in each sector. In Figure 14, the upper panel shows the measure of skewness of the growth rate of employment (right panel). For comparison, the left panel shows the annual growth rate of sales. Both series move very close to each other. The lower panel of the figure shows the 90th to 50th and 50th to 10th percentile differential. At industry level, the figure is quite similar, as is shown in Figure 28. The skewness of the employment growth in sectors like Services, Construction and Trade shows cyclical patterns very similar to those found in

FIGURE 13 – Skewness of Gross Profits



the aggregate data.

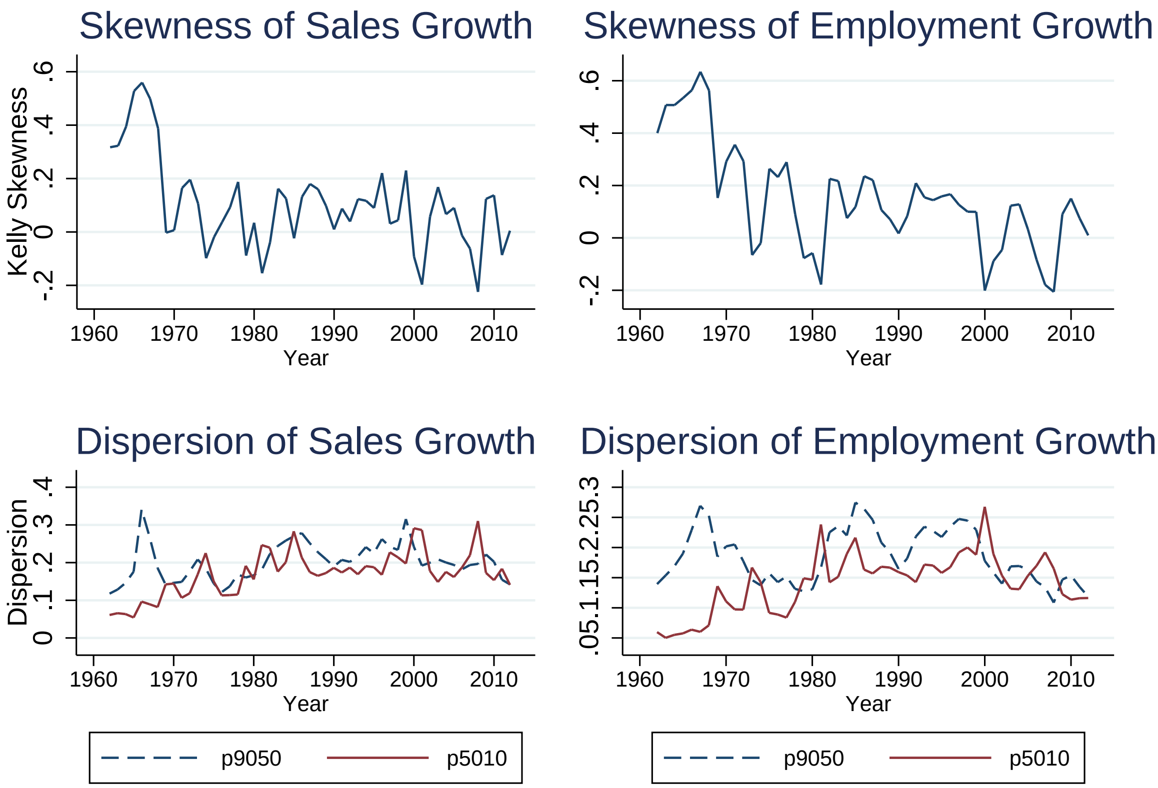
5 Panel analysis

5.1 Higher order moments and size distribution

The analysis so far provides a look to how sales growth shocks vary over the business cycle. However, we can imagine that the properties of sales growth shock vary systematically with firm level characteristics. In particular, it may be possible that small firms face a different sales shocks than large firms. In this section we exploit the panel dimension of our sample to answer the following questions: how the moments of the growth sales distribution varies with firm's size? how these moments differ between recessions and expansions? And finally, how the distribution differs between transitory shocks and more persistent shocks?

To this end, we study the conditional moment of the sales growth rate distribution using a panel of Compustat firms that have at least 10 years of data. Using the annual data of employment, we construct for each firm i in year t a five-years average employment measured as the mean between $t-1$ and $t-5$. This employment measure is merged with our data of quarterly sales growth data used in the previous sections. Then, we pool all the quarter-firm observations in which the economy is in a recession together,

FIGURE 14 – Skewness of Gross Profits Employment Growth and Annual Sales



and in a different pool we group all the quarter-firm observations in which the economy is in a expansion. As before, we use the NBER dates to define an recession. These two samples are divided in 100 percentiles, and then, for each of these binds we calculate different moments of the sales growth distribution (i.e. $P9010$, Kelly's skewness, etc.). The properties of this conditional distribution will be informative of the nature of the within-group variation of the sales growth distribution. Here we define a transitory shock as the growth rate between quarter t and $t+4$ (one year ahead) while a permanent shock is defined as the growth rate between t and $t+20$ (5 years ahead).[7]

The first set of results refers to conditional dispersion of the growth rate of sales distribution. The figure 15 shows, from top to bottom, the 90th, 50th and 10th percentile of the distribution of the transitory shocks, $g_{t,t+4}$ against each percentile of the five-year

[7]Each of the graphs shown the results of an smoothing procedure using a locally weighted regression method. We set the bandwidth to 0.7 although the results do not change substantially if we use other values for the bandwidth.

average employment separating expansion periods (blue, dashed line) to the recession periods (read, solid line). First notice the variation of these percentiles as we move to the right along the x-axis. Interestingly, the following pattern holds in recession and expansion periods: at any point in time, smaller firms face the largest dispersion of sales growth change. That is, the 90th to 10th percentile differential is widest for these firms and falls moving to the right. Figure 16 shows a similar graph but now the change of sales between t and $t+20$, that is, five years apart (permanent shock). Precisely the same qualitative features are seen here with small firms facing a wider dispersion of growth than bigger firms. However, the differences between recessions and expansion are less evident in this case.

Figure 15 – Percentiles of the sales growth distribution (Transitory Shock, $g_{t,t+4}$)

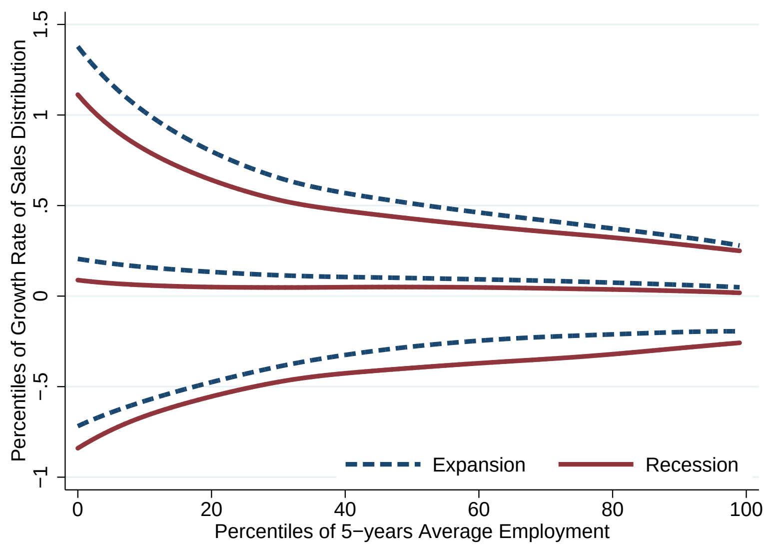
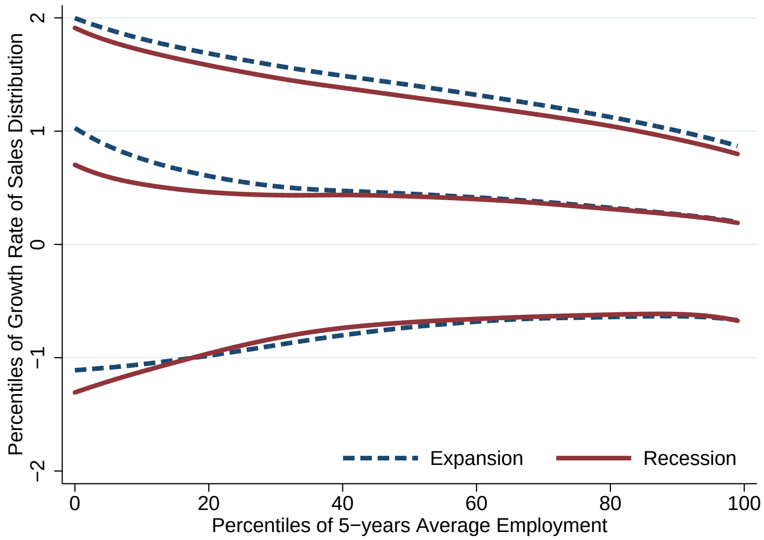


FIGURE 16 – Percentiles of the sales growth distribution (Permanent Shock, $g_{t,t+20}$)



Now we turn to higher order moments of the distribution of sales growth conditional on the size of the firm. Figure 17 displays the skewness of the cross sectional distribution (Kelly's skewness). There are at least two things to notice in this graph. First, the level of the skewness is much lower during recessions than expansion for all size levels. This confirms what we have found before, that is, recessions are periods in which the dispersion increases but the increment mostly happens in the left tail of the distribution. Second, the skewness declines sharply as we move from the left to the right of the size distribution, that is, large firms seems to suffer shocks that are consistently more left skewed than small firms. For completeness, figure 18 shows the same cross sectional moment for the permanent shock. Interestingly, this shows a completely different patter, increasing, instead of decreasing, as we move from the bottom of the distribution to the top. A different way to look at the same phenomena is to look at the dispersion above and below the median separately. Figures 19 to 22 shows the $P90-50$ and $P50-10$ differential for the transitory and permanent shock.

FIGURE 17 – Skewness of the sales growth distribution (Transitory Shock, $g_{t,t+20}$)

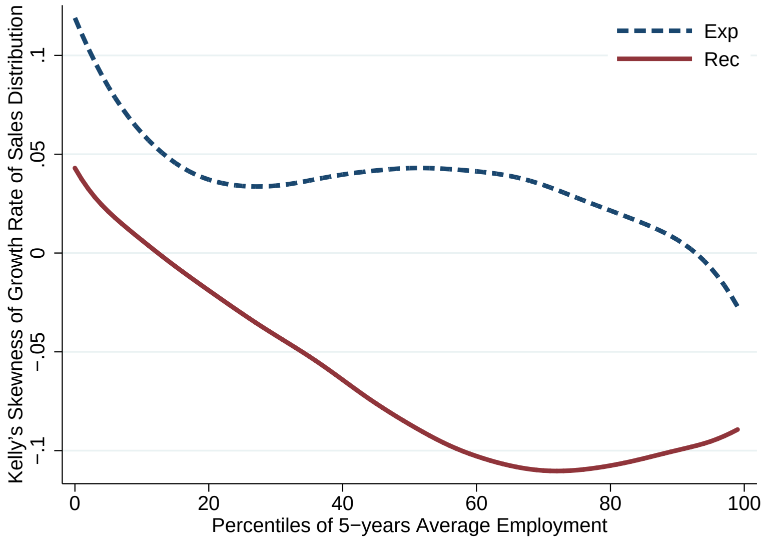


FIGURE 18 – Skewness of the sales growth distribution (Permanent Shock, $g_{t,t+20}$)

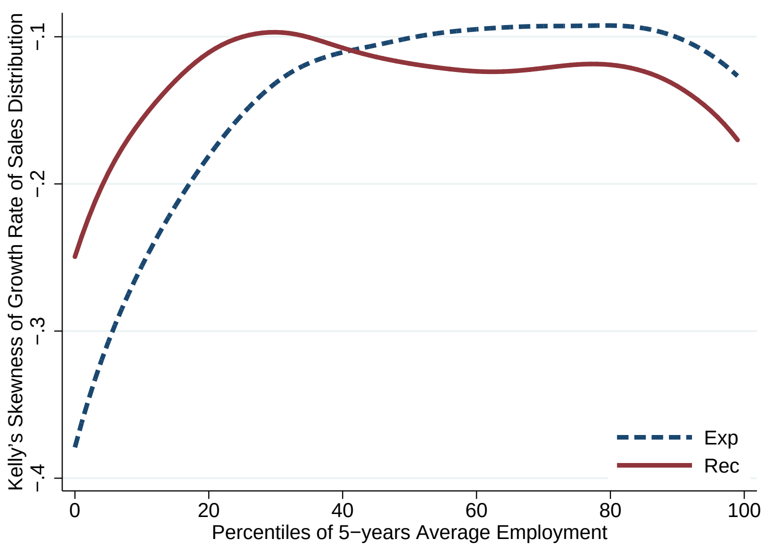


Figure 19 – Upper Dispersion of the sales growth distribution (Transitory Shock, $g_{t,t+4}$)

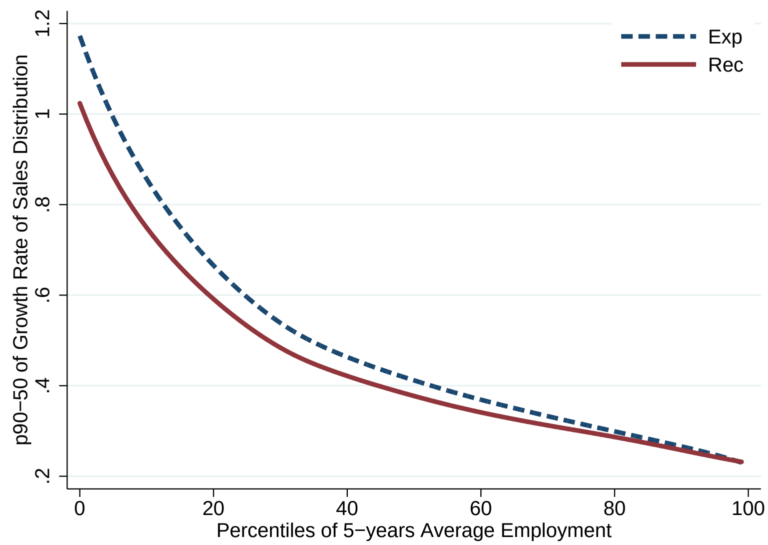


Figure 21 – Upper Dispersion of the sales growth distribution (Permanent Shock, $g_{t,t+20}$)

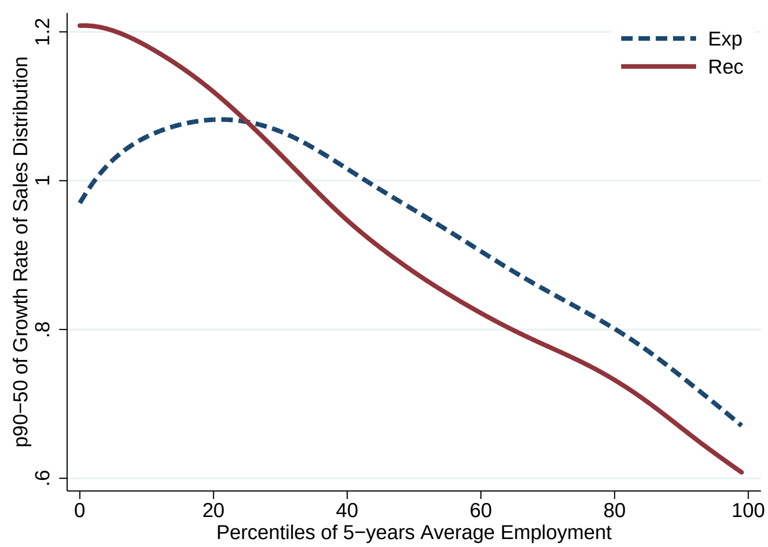


Figure 20 – Lower Dispersion of the sales growth distribution (Transitory Shock, $g_{t,t+4}$)

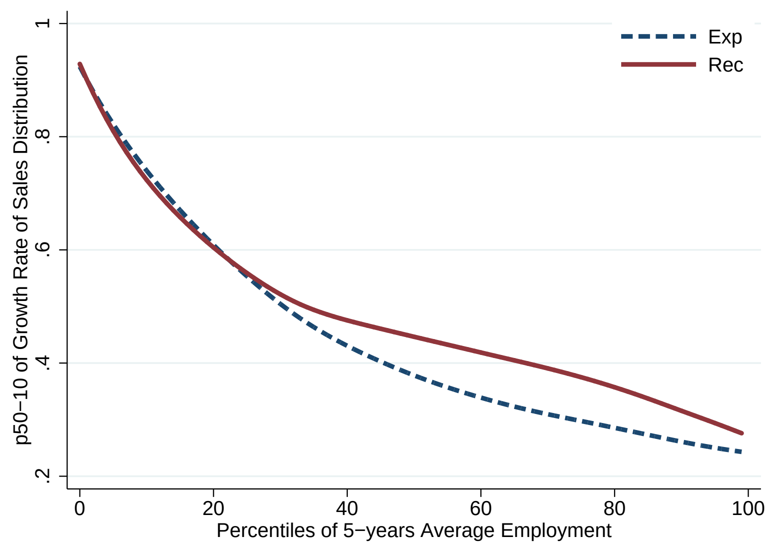
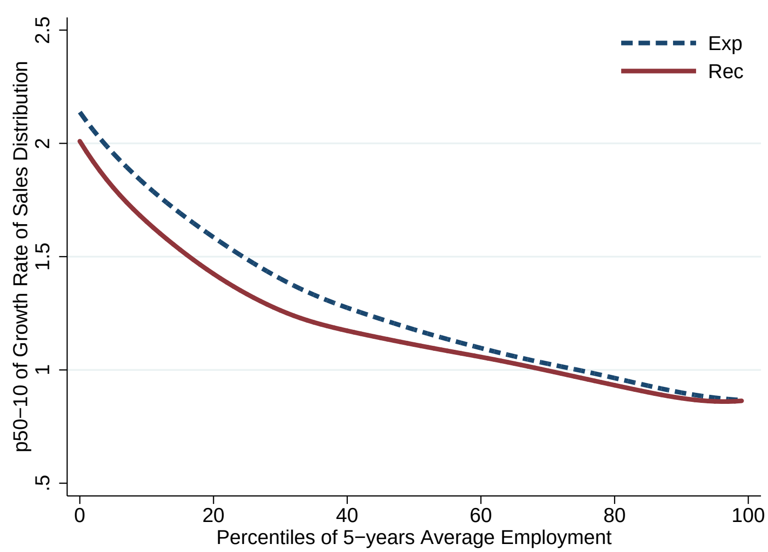


Figure 22 – Lower Dispersion of the sales growth distribution (Permanent Shock, $g_{t,t+20}$)



In previous sections we have shown that the kurtosis of the cross sectional sales growth distribution is not only leptokurtic but also that varies with the cycle. To add to this evidence, figures 23 and 24 show how the kurtosis varies with the firm's size. Figure 23 displays the coefficient of kurtosis conditional of the size of the firm for a transitory sales growth shock. The first thing to notice is the large increase of the kurtosis as we move from left to right: from the bottom to the top of the distribution of employment the kurtosis of the transitory shock increases three times from around 4 to 12, implying that the excess of kurtosis increases more than 10 times. The same pattern can be found in the case of the permanent shock as is shown in figure 24. Notice, however, that the scale of kurtosis is near of 3, as one would expect from a Gaussian distribution.

The take off of this section is that small and large firms face shocks that differ substantially and this difference goes beyond the well establish fact that small firms are, in general, more volatile, in terms of their outcomes and productivity, than large firms. As our analysis shows, dispersion is not the only dimension in which the sales growth distribution differs across groups. In particular, small firms face almost symmetrical shocks that do not differ much to what one would expect from a Gaussian distribution, while large firms face negative skewed shocks which are highly leptokurtic.

FIGURE 23 – Kurtosis of the sales growth distribution (Transitory Shock, $g_{t,t+4}$)

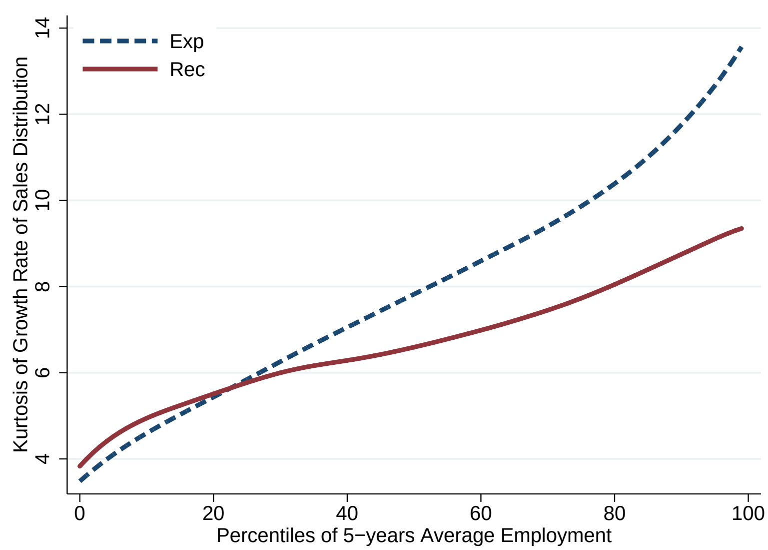
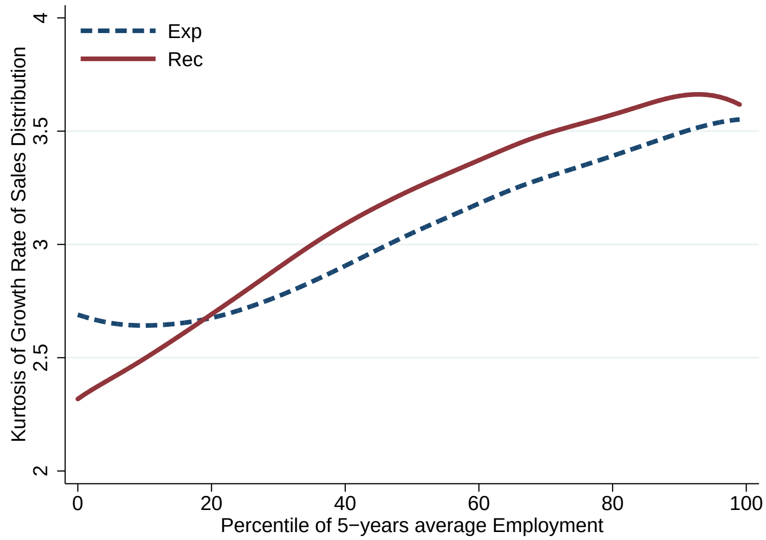


Figure 24 – Kurtosis of the sales growth distribution (Permanent Shock, $g_{t,t+4}$)



5.2 Firm level time series

How much the changes in the cross sectional moments of firm level outcomes tell us about the risk a particular firm? It might be possible, for instance, that a decline in the skewness of sales growth is coming from a change in the mean of the distribution of the growth rate of sales at firm level. In other words, the changes of the cross sectional distribution might not be a reflection of changes in the risk faced by the firm since the former could be generated a simple change in the mean growth rate of a set of firms. In this section we study if the time series of firm level growth rates present higher order moments that deviate from a Gaussian distribution. We focus our analysis in the residuals of the following linear regression,

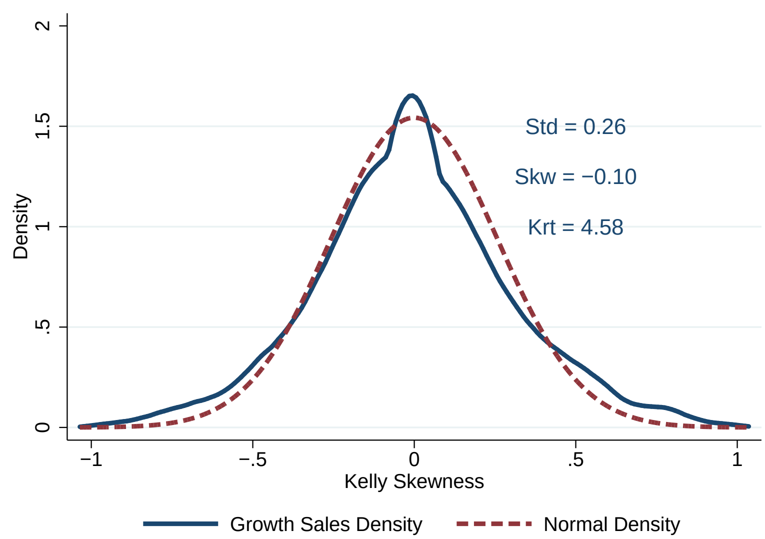
$$g_{it} = \rho g_{it-1} + X_{it}\beta + \epsilon_{it},$$

in which ρ is common for all firms and X_t is a set of variables to control for fixed effects, age, industry, etc.[8] We estimate ρ using and the rest of the parameters using OLS with robust standard errors. We found a value of ρ ranging from 0.60 to 0.64. Using the estimated parameters we get a sample of $\widehat{\epsilon_{it}}$ – a sample of the innovations of the firm level sales growth process – from which we can calculate different moments. For instance, we

[8]We have tried several different specifications and variables. The results presented here do not change substantially across them.

could calculate the Kelly's Skewness as we did with our cross sectional sample of firms. That is, for each firm i we have have one observation of the Kelly skewness, KSK_i. Then, we can study the characteristics of the cross sectional distribution of the Kelly's Skewness. For instance, one could expect that if the innovations at firm level are drawn from a Gaussian distribution, the cross sectional distribution of KSK_i will be centered around 0 and having low variance and high kurtosis. Figure 25 shows the density of the distribution of KSK_i for our sample of Compustat firms with more than 10 years of data. The first thing to notice is that the resulting distribution is very close to a normally distributed random variable – we cannot reject the null hypothesis that the distribution of normal using a standard normality test. Secondly, given the normality results, an standard deviation of 0.26 implies that approximately 5% of the firms in our sample have innovations with an skewness lower than -0.42. Notice that these are not driven by age or industry effects since we have controlled for that in the estimation.

FIGURE 25 – Cross Sectional Distribution of Kelly's Skewness



6 Cross Country Evidence

6.1 Osiris - Industrial

6.1.1 Sample selection

Osiris is a database containing financial information on globally listed public companies, including banks and insurance firms from over 190 countries. The combined

Table IX – Data Availability O9-Sample

Country	Freq.	Percent	Cumulative	Inic.	End
Australia	9,062	3.01	3.01	1984	2013
Canada	21,998	7.3	10.3	1983	2013
China	16,110	5.34	15.64	1991	2013
France	10,809	3.58	19.23	1983	2013
Germany	10,196	3.38	22.61	1983	2013
India	14,340	4.76	27.36	1984	2013
Japan	31,662	10.5	37.86	1984	2013
Malaysia	12,800	4.24	42.11	1984	2013
Korea	31,899	10.58	52.69	1983	2013
Taiwan	11,453	3.8	56.49	1984	2012
United Kingdom	22,893	7.59	64.08	1983	2013
United States	108,321	35.92	100	1982	2013
Total	301,543	100			

industrial company data set contains standardized and as reported financial information, for up to 20 years on over 80,000 companies. Here, we use the Industry data set from which we extract series of Gross and Net Sales, Number of Employes, and Cost of Goods Sold.

We select the sample of firms as follows. We drop all observations with missing or negative Net Sales. We also drop all observation with missing NAICS or with NAICS and public companies (NAICS above 9200). This give us a sample of 764,952 observations in 147 countries, although, most of them have a small number of year-firm observations (less than 1000). Once this cleaning is done the growth rate of annual sales us calculated as the arc-percent change of sales between t and $t+1$. Then, we further restrict the sample to observations between 1984 and 2013 and to those firms with at least 10 years of data, that is, at least 10 observations for the growth rate of sales, not necessarily continuous, giving us a sample 435,550 year-firm observations. From this sample, we keep those countries that have at least 9000 year - firm observations This restrict the sample to 301,543 observations in 12 countries between 1984 and 2014. The table IX shows the distribution of observations for this sample across countries.[9]This data is complemented using real GDP growth per capita and Unemployment Rate from World Development Indicators, WDI.

[9]For several bins year-country, the number of observations is very small (less than 100 observations), especially before 2000. We will have this into account when we present the results using this data.

6.1.2 Results

In this section we show a set of results using the sample of countries described above. The main findings of the analysis are three: first, there is a robust comovement between the skewness, measured by the Kelly's skewness, and the economic activity, measured by the growth rate of GDP per capita, second we do not find strong evidence of counter cyclical dispersion in the data, and third, we do not find a statistically significant relation between the dispersion below the median and the business cycle, although the correlation has the expected negative sign.

Skewness

The figures 29 and 30 show the evolution of our measure of skewness (left axis, solid line) and the annual growth rate of GDP per capita from the WDI (right axis, dashed line). Two remark here, first, skewness is time varying, as in our sample of U.S. Compustat firms. Secondly, skewness seems to be correlated with the business cycle, especially for U.S. as expected, United Kingdom, Canada, Japan, and Korea. These are exactly the countries for which we have more observations as is shown in table IX. Tables X and XI show the correlation between the growth of GDP per capita and our measure of skewness. The correlation has the expected positive sign for most of the countries with the exception of China and India.[10]

Table X – GDP Growth and Kelly's Skewness - Diff Countries

	(1) USA	(2) CAN	(3) GBR	(4) AUS	(5) DEU	(6) FRA
β_{gGDP}	4.501***	2.689	3.601***	1.979	3.064***	4.370***
	(4.41)	(1.39)	(6.61)	(1.08)	(4.03)	(4.79)
$Cons$	0.0818*	0.119*	0.0320	0.0615	0.0216	0.0409*
	(2.72)	(2.38)	(1.52)	(1.22)	(0.96)	(2.26)
R^2	0.436	0.0881	0.413	0.0307	0.153	0.314
N. Obs	30	30	30	29	29	29

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[10]For all the regression analysis of this section we use a robust estimator of the variance - covariance matrix. For additional robustness, we run the same set of regressions using a robust estimator (*rreg* command in STATA), using bootstrapped standard errors and robust estimation of the variance covariance matrix to control for potential heteroscedasticity and autocorrelation (*newey* command in STATA). We do not find any significant change in the point estimates, however, the statistical significance changes for some countries, like Japan.

Table XI – GDP Growth and Kelly's Skewness - Diff Countries

	(1)	(2)	(3)	(4)	(5)	(6)
	JPN	*KOR*	*CHN*	*IND*	*MYS*	*TWN*
β_{gGDP}	2.073	3.086***	-3.615	-1.391	2.666**	3.453**
	(1.19)	(5.42)	(-1.54)	(-1.43)	(3.31)	(1.487)
Cons	0.0595*	-0.0150	0.367	0.0838	-0.0905*	-0.371
	(2.25)	(-0.40)	(1.74)	(1.82)	(-2.63)	(0.051)
R^2	0.114	0.573	0.114	0.0510	0.357	0.145
N. Obs	24	23	21	24	24	24

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dispersion

Now we turn to our measure of dispersion. Figure 31 and 32 shows the evolution of the 90th to 10th percentile differential of the cross sectional distribution of sales growth rates for different countries (left axis, solid line) and the growth rate of GDP per capita (right axis, dashed line). Interestingly, we do not find strong evidence of counter cyclical dispersion for most of the countries, included U.S. and Canada, as shown in table XII but only for Korea, as shown in table XIII.

Table XII – GDP Growth and Dispersion ($p9010$) - Diff Countries

	(1)	(2)	(3)	(4)	(5)	(6)
	USA	*CAN*	*GBR*	*AUS*	*DEU*	*FRA*
β_{gGDP}	-0.187	-0.191	0.687	-1.404	-1.636	1.601
	(-0.13)	(-0.10)	(0.82)	(-0.44)	(-1.82)	(1.19)
Cons	0.648***	0.745***	0.519***	0.768***	0.431***	0.364***
	(28.76)	(19.26)	(19.79)	(9.73)	(17.34)	(13.21)
R^2	0.000	0.000	0.0126	0.00684	0.0473	0.0456
N. Obs	31	30	30	29	30	30

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Upper and lower dispersion

Finally, we study the evolution of the dispersion above and below the median. Figures 33, 34, and 35 display the time series of the dispersion above the median ($p9050$, right axis, solid line) and below the median ($p5010$, right axis, dashed line). In western countries, the dispersion below the median increases during recessions, however, in this

Table XIII – GDP Growth and Dispersion ($p9010$) - Diff Countries

	(1) JPN	(2) KOR	(3) CHN	(4) IND	(5) MYS	(6) TWN
β_{gGDP}	3.988	-4.093**	-4.922	3.506	-0.519	-0.894
	(1.19)	(-3.63)	(-1.65)	(1.74)	(-0.90)	(0.645)
$Cons$	0.232***	0.658***	1.029***	0.364**	0.719***	0.568***
	(5.82)	(12.82)	(3.98)	(3.15)	(25.39)	(0.244)
R^2	0.142	0.307	0.203	0.0891	0.0511	0.061
N. Obs	29	30	22	27	29	24

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

sample the dispersion above the median seems to decline during recessions and increases during economic booms (see U.S. for instance in figure 33). This evidence partially explains the results of the previous section. The results for Asia are mixed, probably due to small sample size . As before, we run a series of regressions to see if there is any relation between our measures of dispersion and the business cycle. In this case, for the countries like China, India, Taiwan and Malaysia, we use data from 1990 onwards. The results for the dispersion above the median are shown in table XIV and XV. In this sample, seems that the upper dispersion is positively correlated with the business cycle in most the countries under consideration. In the other hand, the dispersion below the median shows the expected negative correlation with the GDP growth in most of the countries, however, the relation is not statistically strong neither for the Western countries nor the Asian countries as can be seen in tables XVI and XVII.

Table XIV – GDP Growth and Upper Dispersion ($p9050$) - Diff Countries

	(1) USA	(2) CAN	(3) GBR	(4) AUS	(5) DEU	(6) FRA
β_{gGDP}	1.389	0.946	1.340**	-0.224	-0.121	1.819*
	(1.55)	(0.89)	(2.84)	(-0.12)	(-0.22)	(2.47)
$Cons$	0.351***	0.411***	0.268***	0.409***	0.222***	0.189***
	(23.15)	(19.92)	(17.46)	(8.99)	(14.08)	(13.29)
R^2	0.0553	0.0277	0.130	0.000566	0.000517	0.151
N. Obs	31	30	30	29	30	30

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE XV – GDP Growth and Upper Dispersion ($p9050$) - Diff Countries

	(1) *JPN*	(2) *KOR*	(3) *CHN*	(4) *IND*	(5) *MYS*	(6) *TWN*
β_{gGDP}	0.0852	-0.00563	-3.007	1.666	0.399	0.476
	(0.49)	(-0.01)	(-1.97)	(1.94)	(1.35)	(0.487)
Cons	0.124***	0.305***	0.576***	0.220***	0.333***	0.273***
	(21.85)	(13.47)	(4.46)	(4.10)	(25.64)	(15.51)
R^2	0.00576	0.000	0.271	0.126	0.0954	0.023
N. Obs	24	24	22	24	24	24

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE XVI – GDP Growth and Lower Dispersion ($p5010$) - Diff Countries

	(1) *USA*	(2) *CAN*	(3) *GBR*	(4) *AUS*	(5) *DEU*	(6) *FRA*
β_{gGDP}	-1.576*	-1.137	-0.653	-1.179	-1.515**	-0.218
	(-2.23)	(-0.86)	(-1.62)	(-0.73)	(-3.40)	(-0.32)
Cons	0.298***	0.334***	0.251***	0.358***	0.210***	0.176***
	(19.62)	(10.39)	(19.53)	(8.69)	(17.73)	(12.31)
R^2	0.151	0.0337	0.0451	0.0153	0.226	0.00384
N. Obs	31	30	30	29	30	30

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Euro Zone and LATAM

One of the main problems of the previous analysis is the small sample size. To address this issue we can go level of aggregation above and pool all firms which their head quarters are in a country of European Union.[11] This give us a sample of 73,883 year-firm observations with an average of 2,300 observations per year from 1983 to 2014 and more than 2,800 observations per year in the period 1990-2013. Then, we calculate the cross sectional moments over this sample. Figure 36 displays the time series of Kelly's skewness, the different measures of dispersion, and the growth rate of GDP per capita from the WDI. Two remarks here, first our result of pro cyclical skewness is robust to this aggregation and second, we still find pro cyclical dispersion, in overall the sample (see

[11]The countries in this sub sample are Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and United Kingdom.

Table XVII – GDP Growth and Lower Dispersion ($p5010$) - Diff Countries

	(1) JPN	(2) KOR	(3) CHN	(4) IND	(5) MYS	(6) TWN
β_{gGDP}	-0.372	-1.709***	-1.915	2.129*	-1.548***	-1.371**
	(-0.56)	(-4.46)	(-1.25)	(2.68)	(-5.41)	(0.527)
$Cons$	0.114***	0.317***	0.452**	0.195**	0.407***	0.295***
	(12.55)	(28.31)	(3.27)	(3.76)	(35.90)	(0.020)
R^2	0.0393	0.490	0.100	0.180	0.423	0.226
N. Obs	24	24	22	24	24	24

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

$p9010$) and above the median ($p9050$) but counter cyclical dispersion below the median ($p5010$). This can be observed in table XVIII that shows a set of regressions of the cross sectional moments on the growth rate of GDP per capita.

Table XVIII – Cross Sectional Moment and GDP Growth - European Union

	(1) $p9010$	(2) $p7525$	(3) KSK	(4) $p9050$	(5) $p5010$	(6) Kur
β_{gGDP}	0.602	0.00865	5.296***	1.642	-1.040*	-38.30
	(0.50)	(0.01)	(5.40)	(2.04)	(-2.44)	(-0.75)
$Cons$	0.453***	0.185***	0.0113	0.229***	0.224***	15.56***
	(17.18)	(14.90)	(0.44)	(13.18)	(21.48)	(12.24)
R^2	0.0128	0.000	0.460	0.185	0.166	0.0225
N. Obs	31	31	31	31	31	31

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Additionally, we can select firms that belong to any LATAM country. Most of the firms in this case are in Mexico, Brazil, or Chile. I restrict the sample to observations between 1997 to 2013. This gives us a sample of 20,140 observations with an average of approximately 1,100 observations per year. Then we correlate the moments calculated over this sample on the growth of GDP per capita of all LATAM countries from WDI. The results are shown in table XIX.

Using Annual Compustat Data

In the previous section we found strong evidence of pro cyclicality of the skewness of the cross sectional distribution of growth rate of sales in a wide sample of countries,

Table XIX – Cross Sectional Moment and GDP Growth - LATAM

	(1)	(2)	(3)	(4)	(5)	(6)
	$p9010$	$p7525$	KSK	$p9050$	$p5010$	Kur
β_{gGDP}	0.153	0.0629	1.097*	0.350	-0.197	4.456
	(0.32)	(0.27)	(2.24)	(1.56)	(-0.66)	(0.20)
$Cons$	0.509***	0.209***	0.0367	0.263***	0.246***	13.96***
	(27.62)	(24.51)	(1.50)	(30.04)	(18.47)	(21.13)
R^2	0.00588	0.00477	0.169	0.128	0.0193	0.00336
N. Obs	16	16	16	16	16	16

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XX – Cross Sectional moments - United States - Annual Data

	(1)	(2)	(3)	(4)	(5)	(6)
	$p9010$	$p7525$	KSK	$p9050$	$p5010$	Kur
β_{gGDP}	-1.436**	-0.757**	4.294***	-0.00294	-1.433***	118.0***
	(-2.75)	(-3.30)	(5.02)	(-0.01)	(-4.16)	(3.51)
$Cons$	0.403***	0.170***	0.0118	0.202***	0.200***	15.61***
	(33.41)	(27.82)	(0.53)	(34.26)	(21.82)	(21.58)
R^2	0.123	0.211	0.318	0.00000194	0.274	0.188
N. Obs	50	50	50	50	50	50

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

however, we did not find counter cyclical dispersion. This is an odd results especially because for the U.S.. Here we contrast the findings using the Osiris data base with a set of results using the annual fundamentals data base from Compustat. This provides a bigger sample of firms for a longer period of time. Table XX shows a set of regressions of our cross sectional moments and the growth rate of GDP per capita from WDI using data from 1964 to 2013. Additionally, to have a direct comparison with the period of time covered by Osiris, table XXI shows similar regressions using data from 1984 to 2013. Jointly, these two tables show that the evidence of counter cyclical dispersion seems to depend on the period of time under consideration, or more precisely, on the presence of recessions in the sample. To see this, observe that when we restrict the sample from 1964 to 1983, and therefore, we remove the Double Dip recession, the correlation between the measures of dispersion become weaker. Interestingly, this is not the case for our measure of skewness.

Table XXI – Cross Sectional moments - United States - Annual Data

	(1) $p9010$	(2) $p7525$	(3) KSK	(4) $p9050$	(5) $p5010$	(6) Kur
β_{gGDP}	-0.0168	-0.287	3.738***	0.863***	-0.880	15.63
	(-0.03)	(-0.84)	(4.72)	(3.71)	(-1.84)	(0.62)
$Cons$	0.419***	0.173***	-0.0151	0.204***	0.215***	16.69***
	(22.24)	(18.96)	(-0.72)	(28.87)	(16.14)	(17.65)
R^2	0.000	0.048	0.397	0.198	0.138	0.005
N. Obs	31	31	31	31	31	31

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2 Global Compustat

6.2.1 Sample Selection

Compustat Global is a database of non-U.S. and non-Canadian fundamental and market information on more than 33,900 active and inactive publicly held companies with quarterly data history from 1987. The main advantage of Compustat Global is that it provides normalized comparability across a wide variety of global accounting standards and practices. Here we describe the selection of the sample of firms that we will use in the analysis. The main variable is the measure of quarterly sales, SALEQ. We drop all the firm-quarter observation with negative net sales or with an empty value in SALEQ. We also drop all the firm with NAIC codes above 9200. Data prior 1997 is very sparse (in average, less than 50 observations per year) and therefore, all the observations prior 1998q1 are dropped. This leave us with a sample of 676,999 firm-quarter observations in 107 countries. Then, a firm will be considered in the baseline sample if it has at least 5 years of data (20 quarters not necessarily continuous). Finally, we keep only those countries which have more than 10,000 observations. This give us a sample of 348,916 in 14 countries. Table XXII shows the distribution of observations in the sample and time span covered in the sample for each country.

Once the cleaning is complete we generate the growth rate of quarterly sales using the arc-percent change between t and $t-4$. We complement this data with the following series: quarterly growth rate (quarter compared with the same quarter of the previous year) of real GDP, real Investment and real Consumption from OECD Stats, and the recessions identifiers provided by the Economic Cycle Research Institute, ECRI, which is available for a small sample of countries. Table XXIII shows the data availability for

Table XXII – Data availability in the R-Sample

Country	Freq.	Percent	Cum.	Inic	End
AUS	39,630	11.36	11.36	1997q3	2013q3
BRA	10,367	2.97	14.33	1997q3	2013q4
CHN	30,017	8.6	22.93	1998q1	2013q4
DEU	16,110	4.62	27.55	1998q1	2013q4
FRA	16,895	4.84	32.39	1998q1	2013q4
GBR	35,393	10.14	42.54	1997q3	2013q4
HKG	25,640	7.35	49.88	1998q2	2013q4
IND	67,408	19.32	69.2	1998q4	2013q4
MYS	28,350	8.13	77.33	1999q1	2013q4
POL	11,635	3.33	80.66	1998q1	2013q4
SGP	17,380	4.98	85.64	1998q1	2013q4
SWE	11,796	3.38	89.02	1998q1	2013q4
THA	15,605	4.47	93.5	1999q2	2013q4
TWN	22,690	6.5	100	2002q1	2013q4
Total	348,916	100			

the set of countries in the baseline sample.

6.2.2 Results

Here we show the results using the baseline sample from Global Compustat. We only consider countries for which we have quarterly GDP growth. For completeness we also show results for the U.S. economy which are coming from Compustat North America. The main conclusions of this section are two, first, we find that the skewness of the distribution of growth rate of sales is pro-cyclical in several countries, and second, there is no evidence of counter cyclical dispersion in European countries. These results confirm what we found using annual data from Osiris.

Skewness

Figures 37 and 38 show the time series of the skewness of the distribution of growth rates of sales (blue solid line, left axis) and the growth rate of real GDP per capita (red dashed line, right axis). The shaded bars are the periods of recessions defined by the ECRI. Because of data availability, different graphs show different time spans.[12] The main message is that the results found in the U.S. economy are also found in this wider sample of countries, that is, skewness is time varying and pro-cyclical. This is confirmed

[12]For each country, the sample starts in the quarter when there are more than 100 observations.

Table XXIII – Data Availability R-Sample

Country	GC	ECRI	Q-GDP
AUS	•	•	•
BRA	•	•	•
CHN	•	•	
DEU	•	•	•
FRA	•	•	•
GBR	•	•	•
HKG	•		
IND	•	•	
MYS	•		
POL	•		•
SGP	•		
SWE	•	•	•
THA	•		
TWN	•	•	

Table XXIV – Skewness and GDP Growth - Global Compustat Sample

	(1) *USA*	(2) *UK*	(3) *DEU*	(4) *FRA*	(5) *POL*	(6) *SWE*	(7) *AUS*	(8) *BRA*
$\beta_{g_{GDP}}$	5.137***	2.156***	2.516***	7.166***	5.762***	1.569**	5.800**	3.692***
	(13.00)	(6.49)	(6.46)	(11.70)	(4.86)	(3.27)	(2.93)	(4.60)
Cons	-0.0825***	0.0861***	-0.00215	-0.00204	-0.226***	0.157***	-0.124	-0.142***
	(-5.78)	(5.20)	(-0.07)	(-0.16)	(-5.31)	(8.34)	(-1.66)	(-3.66)
R^2	0.523	0.100	0.152	0.716	0.405	0.178	0.149	0.248
N. Obs	60	56	36	36	39	36	61	60

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$

by table XXIV in which we show a series of regressions of our measure of skewness on the growth rate of GDP per capita for different countries. [13] For all countries, the coefficient of the growth rate of GDP per capita is positive and significant. One finds similar results when one uses the growth rate of investment, shown in table XXV, or the growth rate of consumption, shown in table XXVI.

[13]Throughout this section, regressions are calculated using a robust estimation of the matrix of variance - covariance. For additional robustness, we run each regression using the Newey - West estimator of the matrix of variance - covariance with two lags (command newey in Stata), estimating the standard errors using bootstrap, and using a robust estimator (command rreg in Stata). The changes are minimal.

Table XXV – Skewness and Investment Growth - Global Compustat Sample

	(1) *USA*	(2) *UK*	(3) *DEU*	(4) *FRA*	(5) *POL*	(6) *SWE*	(7) *AUS*	(8) *BRA*
β_{gGDP}	1.665***	0.522	1.160***	2.894***	1.757***	0.795**	0.638	1.181***
	(8.64)	(1.66)	(4.70)	(10.95)	(7.13)	(3.55)	(1.49)	(5.73)
$Cons$	-0.00376	0.120***	0.0110	0.0407**	-0.102***	0.165***	0.0241	-0.0726**
	(-0.30)	(6.69)	(0.35)	(3.11)	(-4.21)	(8.85)	(0.61)	(-2.96)
R^2	0.459	0.0409	0.107	0.701	0.524	0.207	0.0536	0.336
N. Obs	60	56	36	36	39	36	61	60

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$

Table XXVI – Skewness and Consumption growth - Global Compustat Sample

	(1) *USA*	(2) *UK*	(3) *DEU*	(4) *FRA*	(5) *POL*	(6) *SWE*	(7) *AUS*	(8) *BRA*
β_{gGDP}	5.137***	2.156***	2.516***	7.166***	5.762***	1.569**	5.800**	3.692***
	(13.00)	(6.49)	(6.46)	(11.70)	(4.86)	(3.27)	(2.93)	(4.60)
$Cons$	-0.0825***	0.0861***	-0.00215	-0.00204	-0.226***	0.157***	-0.124	-0.142***
	(-5.78)	(5.20)	(-0.07)	(-0.16)	(-5.31)	(8.34)	(-1.66)	(-3.66)
R^2	0.523	0.100	0.152	0.716	0.405	0.178	0.149	0.248
N. Obs	60	56	36	36	39	36	61	60

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$

Dispersion

As in previous sections, we measure dispersion as the 90th to 10th percentile differential. Figures 39 and 40 show our measure of dispersion (solid blue line, left axis) and the growth rate of GDP per capita (dashed red line, right axis) for eight different countries. The top left panel of figure 39 displays the results for U.S.. As expected, the cross sectional dispersion in U.S. increases during recessions, however, this does not seem to be the norm in other countries. To evaluate this, we run a set regressions of our measure of dispersion and the growth rate of GDP per capita. The results shown in table XXVII confirm that counter cyclical dispersion found in U.S. firms but for the rest of the countries the correlation is not statistically significant or even positive, as in UK. Notice, however that this is happening because in most countries, the dispersion shows a declining trend which is only reversed during the last recession (see UK for instance in figure 39), and therefore, is still possible to argue that, as in U.S., the dispersion

Table XXVII – Dispersion ($p9010$) and GDP growth - Global Compustat Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	USA	UK	DEU	FRA	POL	SWE	AUS	BRA
β_{gGDP}	-2.305***	3.540**	-0.457	-0.742	1.124	0.0239	6.095	-0.560
	(-4.66)	(2.82)	(-0.86)	(-1.05)	(1.01)	(0.04)	(1.62)	(-1.17)
$Cons$	0.517***	0.781***	0.534***	0.436***	0.749***	0.821***	1.696***	0.656***
	(37.96)	(19.44)	(25.12)	(23.41)	(11.96)	(26.69)	(13.86)	(24.60)
R^2	0.176	0.100	0.0154	0.0165	0.0189	0.0000253	0.0473	0.0101
N. Obs	60	56	36	36	40	36	61	60

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$

increases during recessions. However with only one recession in the sample for most of the countries, its difficult to establish any statistical relation.

Lower and Upper dispersion

In this section we study if there is any systematic different between the dispersion above and below the median of the distribution of growth rate of sales. Tables XXVIII and XXIX show the results of a regression between the 90th to 50th percentile differential, our measure of dispersion above the median, and the 50th to 10th percentile differential, our measure of dispersion below the median on the growth rate of GDP per capita. The first column of both tables shows the results for U.S., in which, as reported before, we find strong counter cyclical dispersion below the median. What is interesting here is that in most of the countries we find pro cyclical dispersion above the median. Table XXIX shows a set of regressions in which the dependent variable is our measure of dispersion below the median. We find that the variability in the lower part of the distribution is counter cyclical in most of the countries under study.

The Europe Sample

One of the limitations of the country level analysis presented in the previous section is the small sample size. One way to address this problem is to go up one level to aggregation. Here we do this using all firms which headquarters are in Europe.[14] The sample contains 140,209 observations with more than 1,000 observations per year starting in 1999. We complement this data with GDP per capita growth of the OECD.

[14]The sample contains the following countries: CHE, DEU, FRA, GBR, GRC, ITA, NOR, POL, RUS, and SWE.

TABLE XXVIII – Dispersion above the median ($p9050$) and GDP growth - Global Compustat Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	USA	*UK*	*DEU*	*FRA*	*POL*	*SWE*	*AUS*	*BRA*
β_{gGDP}	0.336	3.009***	0.524	1.344**	2.909***	0.699	7.875*	0.877*
	(1.17)	(4.07)	(1.84)	(3.26)	(3.58)	(1.57)	(2.64)	(2.32)
Cons	0.232***	0.429***	0.272***	0.217***	0.284***	0.477***	0.761***	0.283***
	(37.68)	(18.24)	(20.08)	(19.99)	(8.05)	(21.87)	(7.20)	(15.00)
R^2	0.0141	0.184	0.0424	0.130	0.262	0.0388	0.128	0.0641
N. Obs	60	56	36	36	40	36	61	60

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$

TABLE XXIX – Dispersion below the median ($p5010$) and GDP growth - Global Compustat Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	USA	*UK*	*DEU*	*FRA*	*POL*	*SWE*	*AUS*	*BRA*
β_{gGDP}	-2.641***	0.532	-0.981**	-2.085***	-1.785*	-0.675	-1.780	-1.437***
	(-9.92)	(0.98)	(-3.36)	(-5.83)	(-2.55)	(-1.98)	(-0.88)	(-4.01)
Cons	0.286***	0.352***	0.262***	0.220***	0.465***	0.344***	0.935***	0.373***
	(29.59)	(20.14)	(27.90)	(25.22)	(12.49)	(27.65)	(14.45)	(19.43)
R^2	0.453	0.0126	0.293	0.388	0.107	0.0990	0.0139	0.130
N. Obs	60	56	36	36	40	36	61	60

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$

The figures 42 and 43 compare the change of the distribution of growth rates of sales in the sample. The message here is that the increase in dispersion, measured by the standard deviation or by the 90th to 10th percentile differential, is minor compared with the sharp decrease in the skewness in the same period. For instance, from the peak to the trough of the recession, 2008q1 and 2009q2 respectively, the skewness dropped 130% while the dispersion increased less than 5%, measured by the standard deviation or 12%, measured by the 90th to 10th percentile differential. We get a similar picture if we compare the two years prior the recession, 2005-2006 for instance, to the years of the recession, 2008-2009.

A different way to study the data is to compare the time series of the cross sectional moments to the growth rate of GDP per capita. Figure 41 displays the evolution of our measures of skewness, dispersion, and kurtosis for the sample of European firms.

As in the other figures, the solid blue line is the cross sectional moment while the red dashed line is the growth rate of GDP. Since most of the firms in the sample are in United Kingdom, Germany and France, the patterns are similar to those observed in the previous section, in particular, we find that skewness is pro-cyclical and a secular declining trend in the dispersion only reversed by a mild increase during the years of the Great Recession.

Finally, we can run a set of regressions of the cross sectional moments on the growth rate of GDP. Table XXX shows the results.[15] We find that dispersion is pro cyclical in this sample, especially above the median (columns 1 and 4) and, more importantly, skewness is also pro cyclical (column 3). These findings are consistent with what we found in most of the countries studied in the previous section. We can complement this analysis using data of investment and consumption growth. The results concerning investment are shown in table XXXI and those for consumption in table XXXII. Interestingly, the partial correlation of the consumption growth and all the cross sectional moments of the growth of sales is very strong and statistically significant.[16]

Table XXX – Cross Sectional Moment and GDP Growth - Global Compustat Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	$p9010$	$p7525$	KSK	$p9050$	$p5010$	KUR
β_{gGDP}	2.498*	0.626	3.208***	2.679***	-0.182	-23.20*
	(2.49)	(1.59)	(11.31)	(5.00)	(-0.36)	(-2.07)
$Cons$	0.852***	0.320***	0.0656***	0.454***	0.398***	8.635***
	(26.95)	(27.31)	(7.36)	(27.76)	(24.20)	(25.37)
R^2	0.0509	0.0293	0.446	0.195	0.000957	0.0620
N. Obs	56	56	56	56	56	56

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.3 Amadeus - Orbis

6.3.1 Sample Selection

Amadeus - Orbis is a pan-European financial database containing information on 20 million public and private companies from 43 countries, including all the EU countries

[15] These regressions are calculated using a robust estimator of the standard errors. As before, I run a full set of robustness checks. There is not significant changes in the point estimates.

[16] I run similar regressions for United States using the sample of Compustat firms. The results are quite similar.

Table XXXI – Cross Sectional Moment and Investment Growth - Global Compustat Sample

	(1) $p9010$	(2) $p7525$	(3) KSK	(4) $p9050$	(5) $p5010$	(6) KUR
$\beta_{g_{GDP}}$	0.656	0.136	1.555***	1.001***	-0.345	-7.987
	(1.57)	(0.89)	(12.31)	(4.55)	(-1.59)	(-1.87)
$Cons$	0.884***	0.328***	0.0985***	0.485***	0.399***	8.358***
	(28.05)	(30.80)	(10.49)	(30.24)	(23.69)	(30.31)
R^2	0.0171	0.00668	0.509	0.132	0.0167	0.0357
N. Obs	56	56	56	56	56	56

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table XXXII – Cross Sectional Moment and Consumption Growth - Global Compustat Sample

	(1) $p9010$	(2) $p7525$	(3) KSK	(4) $p9050$	(5) $p5010$	(6) KUR
$\beta_{g_{GDP}}$	8.048***	2.576***	4.366***	6.216***	1.832*	-79.45***
	(5.47)	(4.17)	(7.42)	(8.90)	(2.17)	(-4.59)
$Cons$	0.770***	0.290***	0.0506***	0.402***	0.367***	9.470***
	(23.68)	(22.23)	(4.36)	(27.40)	(19.56)	(23.78)
R^2	0.260	0.244	0.407	0.518	0.0479	0.358
N. Obs	56	56	56	56	56	56

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

and Eastern Europe. It provides up to 10 years of detailed information comprising 24 balance sheet items, 25 profit and loss account items and 26 ratios. We use a subset of these variables, in particular, sales, employment, and legal status which will allow us to classify firms between public and private. Amadeus - Orbis is divided in four major categories which dictate the size of the data set. Here we use data from large and very large firms. We complement this data with a classification of firms as public and private provided by Bureau van Dijk. This classification is available for all the major countries in Europe.

The raw sample contains more than 4 millions of year-firm observations from 1985 to 2014. However, the sample size is very small 1997 (less than 1,000 observations per year) and therefore we drop all the observations prior 1997. Additionally we do not consider observations of firms with four digit NAICS greater than 9200. Then we drop all the firms with negative or missing values of sales. Using this sample, we generate three sub samples which are selected as follows, The baseline sample contains firms which are in a country with more than 10,000 firm-year observations. This generates a sample of 1,776,326 firm-year observations in 21 countries. Table XXXIII shows the distribution of observations and the time span for each of the countries in the sample. The second and third samples consider only Public and Private firms respectively as defined by the Bureau van Dijk. Once this cleaning is done, we generate the growth rate of annual sales using the arc-percent change between t and $t+1$. This data set covers a very short time span. For most of the countries we do not have more than 16 years of data between 1997 to 2014 and therefore the regression analysis that we have done using Osiris and Compustat is not feasible. As such, a country-by-country analysis is still informative, especially because Orbis provides information about countries that are not present in other data sets. Additionally, we present results using the whole sample of European firms and a separate set of results for Private and Public firms.

6.3.2 Results

Skewness and dispersion

Figures 44 and 45 display the time series of the skewness of the distribution of sales growth rates and the growth of GDP per capita of a sub set of European countries. Not surprising, here we also find that skewness is pro cyclical.

Dispersion in the other hand shows the expected increase during the Great Recession despite the fact that, in some countries, like Germany, France and Italy, dispersion shows a declining trend. This can be observed in figures 46 and 47 that show the 90th to 10th percentile differential.

As we have done before, we separate the dispersion in a measure of volatility above the median, the 90th to 50th percentile differential of the cross sectional distribution, and below the median, the difference between the 50th and 10th percentiles. These time series are shown in Figures 48 and 49 The results are quite similar to those found on other data sets, that is, during the Great Recession, most of the increase in the dispersion comes mostly from the lower part of the distribution. Furthermore, the dispersion above the median seems to decline during the years of the Great Recession in most of the countries.

Table XXXIII – Distribution of Observations - O10 Sample

Country	Freq.	Percent	Cum.	Inic.	End
Austria	26,010	1.46	1.46	2001	2013
Belgium	77,574	4.37	5.83	1997	2013
Bulgaria	23,387	1.32	7.15	1997	2012
Croatia	12,208	0.69	7.83	1998	2013
Czech Republic	52,550	2.96	10.79	2003	2013
Finland	37,432	2.11	12.9	1997	2013
France	327,083	18.41	31.31	2000	2013
Germany	183,473	10.33	41.64	1998	2013
Greece	20,717	1.17	42.81	2003	2013
Hungary	28,347	1.6	44.4	1998	2013
Italy	302,321	17.02	61.42	1997	2013
Netherlands	37,047	2.09	63.5	1997	2013
Norway	69,095	3.89	67.39	2004	2013
Poland	83,311	4.69	72.08	1997	2012
Portugal	36,709	2.07	74.15	2002	2013
Romania	42,040	2.37	76.52	1997	2012
Serbia	19,217	1.08	77.6	2001	2012
Slovakia	16,430	0.92	78.52	1999	2013
Slovenia	10,167	0.57	79.1	2002	2012
Spain	197,450	11.11	90.21	1997	2013
Sweden	100,040	5.63	95.84	1997	2013
Ukraine	73,867	4.16	100	1999	2012
Total	1,776,475	100			

Europe sample and Private-Public comparison

We can also aggregate the sample one level up and do a European level analysis. This will allow us to increase the number of observations per year. One concern that might arise is that we are comparing firms with different accounting practices, however, Bureau van Dijk standardizes balance sheet information with the explicit purpose to allow cross country comparisons, and hence, the possible bias generated by different accounting practices is minor. Additionally, analyzing a sample of European firms allows us to study differences between public and private firms. This could have been done at country level also but the number of year-firm observation is very small, even for large countries like Germany or France.

Using the sample of European firms we calculate the same set of cross sectional moment discussed previously. Notice that this sample contains more countries than the countries studied in the previous section, in particular, it contains some Eastern European countries which where excluded from the previous analysis because of the sample size.[17]

Figure 50 shows four graphs with the time series of cross sectional moments and the GDP Growth. As expected, the skewness decreased during the Great Recession (upper left panel) while dispersion increases (right upper panel). However, all the increase comes from the left tail of the distribution, that is, by the increase in the in the difference between the 50th and the 10th percentile (see the lower left panel). Additionally, kurtosis seems to decline during the recession (lower right panel). We can also look more closely to the difference in the distribution before and during the Great Recession. To see this, Figure 51 compares the cross sectional distribution of sales growth in 2005 and 2006 (two years before the recession) with the distribution of sales growth during the recession, that is, 2008 and 2009. We also show three cross sectional statistics, the skewness, the standard deviation and the 90th to 10th percentile differential. The main observation here is that the change in skewness is bigger than the change observed in dispersion. In particular, the skewness decreases a 72% while the standard deviation increases only 13% and the 90th to 10th percentiles differential increases a 20%.

Now we turn to a comparison between private and public firms. To do this we categorize each firm between public, private and others using the information provided by Bureau van Dijk and the legal status variable available in Orbis for each firm. we calculate the same set of cross sectional moments separately for each of these sub samples of firms. The results are shown in figure 52. If any, the differences between private and public firms are just in terms of levels.

[17]This countries still have more than 10,000 firm-years observations but concentrated mostly after 2004. The results, however, are quite similar if one considers only those countries presented in the previous section

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FIGURE 26 – Skewness of the Gross Profits Growth in Different Sectors. The solid line is the cross sectional skewness of the distribution of growth rates of sales in each category. The dashed line is the skewness calculated using the base line sample

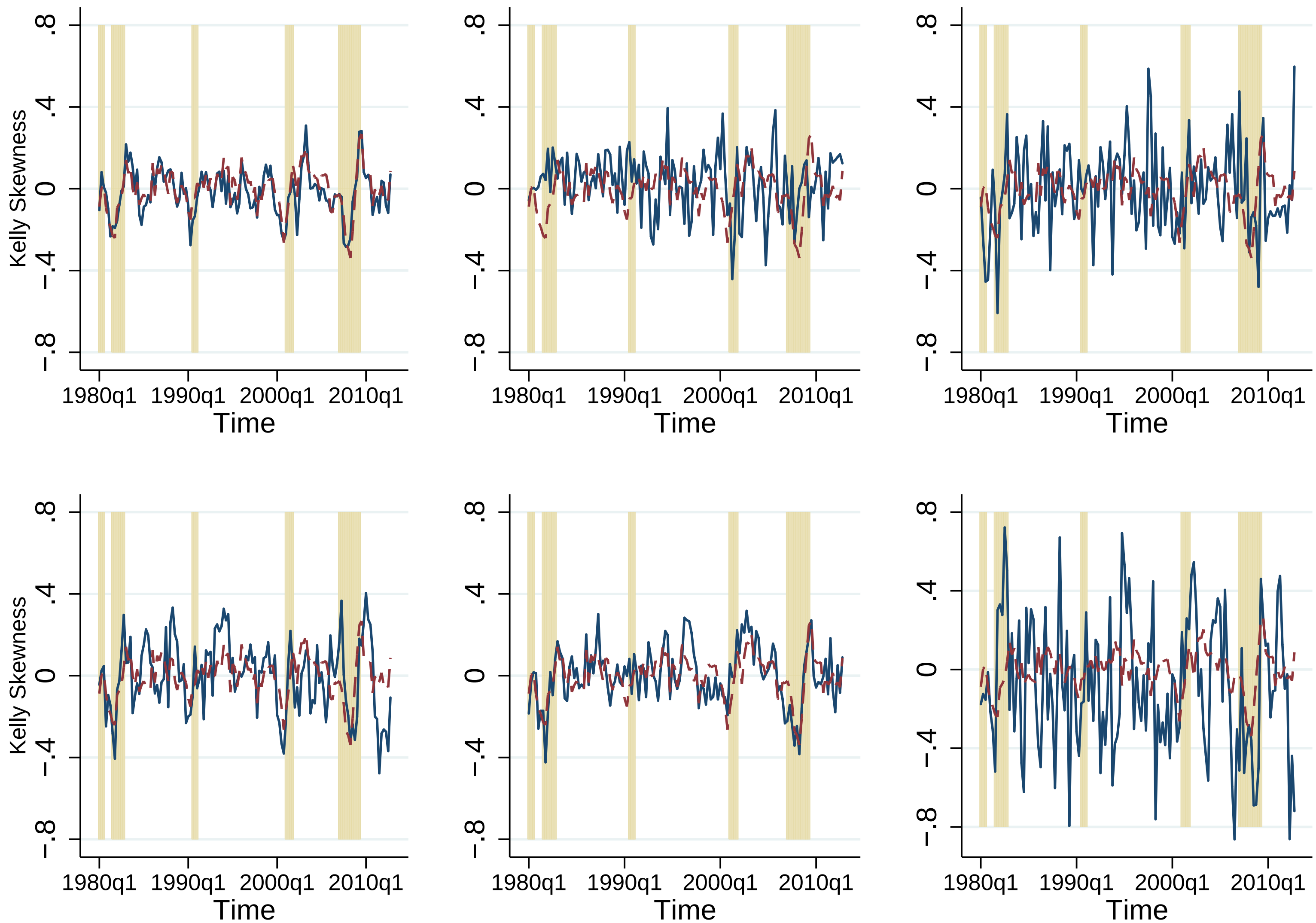

Figure 27 – Skewness of the Annual Sales Growth in Different Sectors. The solid line is the cross sectional skewness of the distribution of growth rates of sales in each category. The dashed line is the skewness calculated using the base line sample

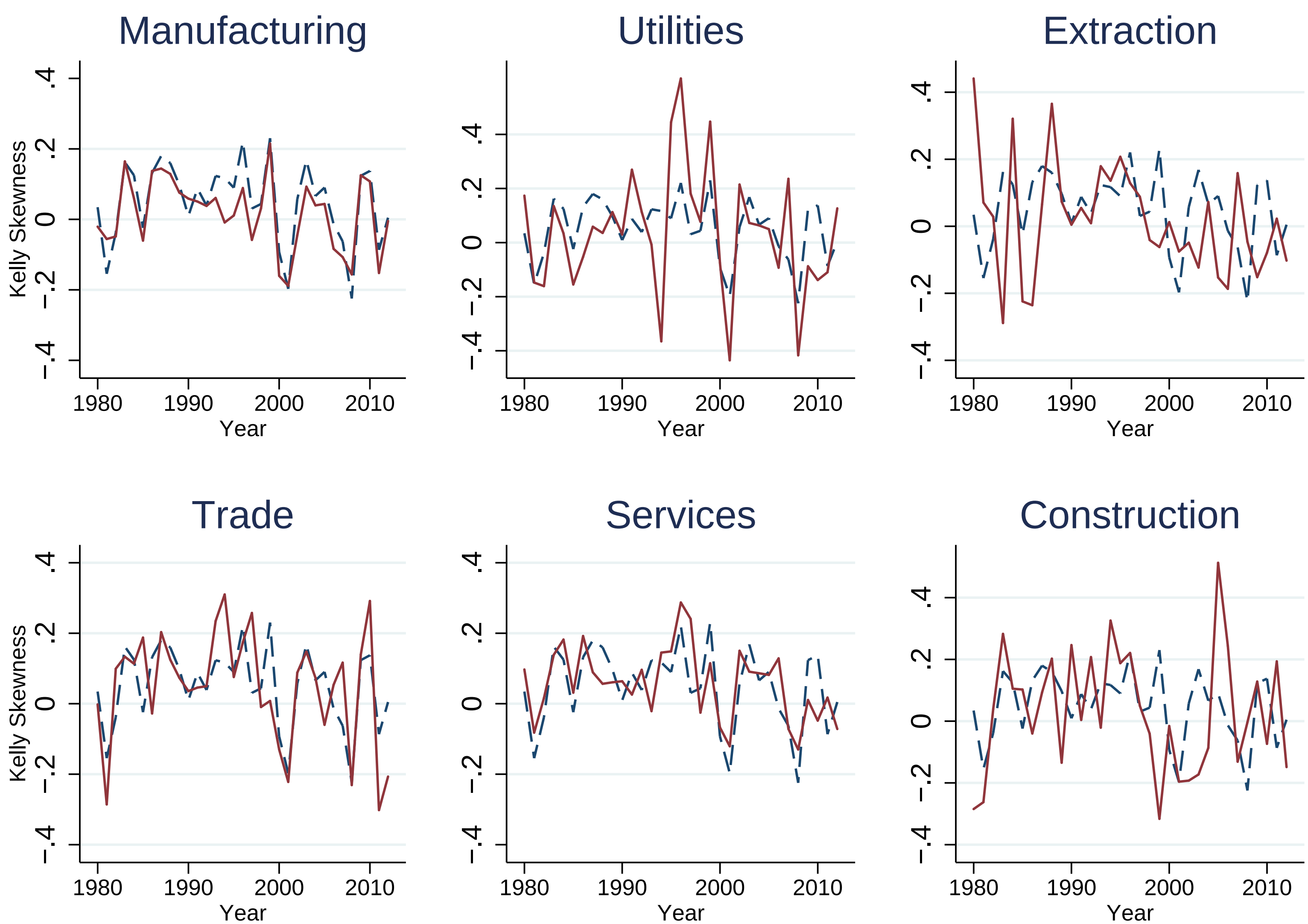

FIGURE 28 – Skewness of the Employment Growth in Different Sectors. The solid line is the cross sectional skewness of the distribution of growth rates of sales in each category. The dashed line is the skewness calculated using the base line sample

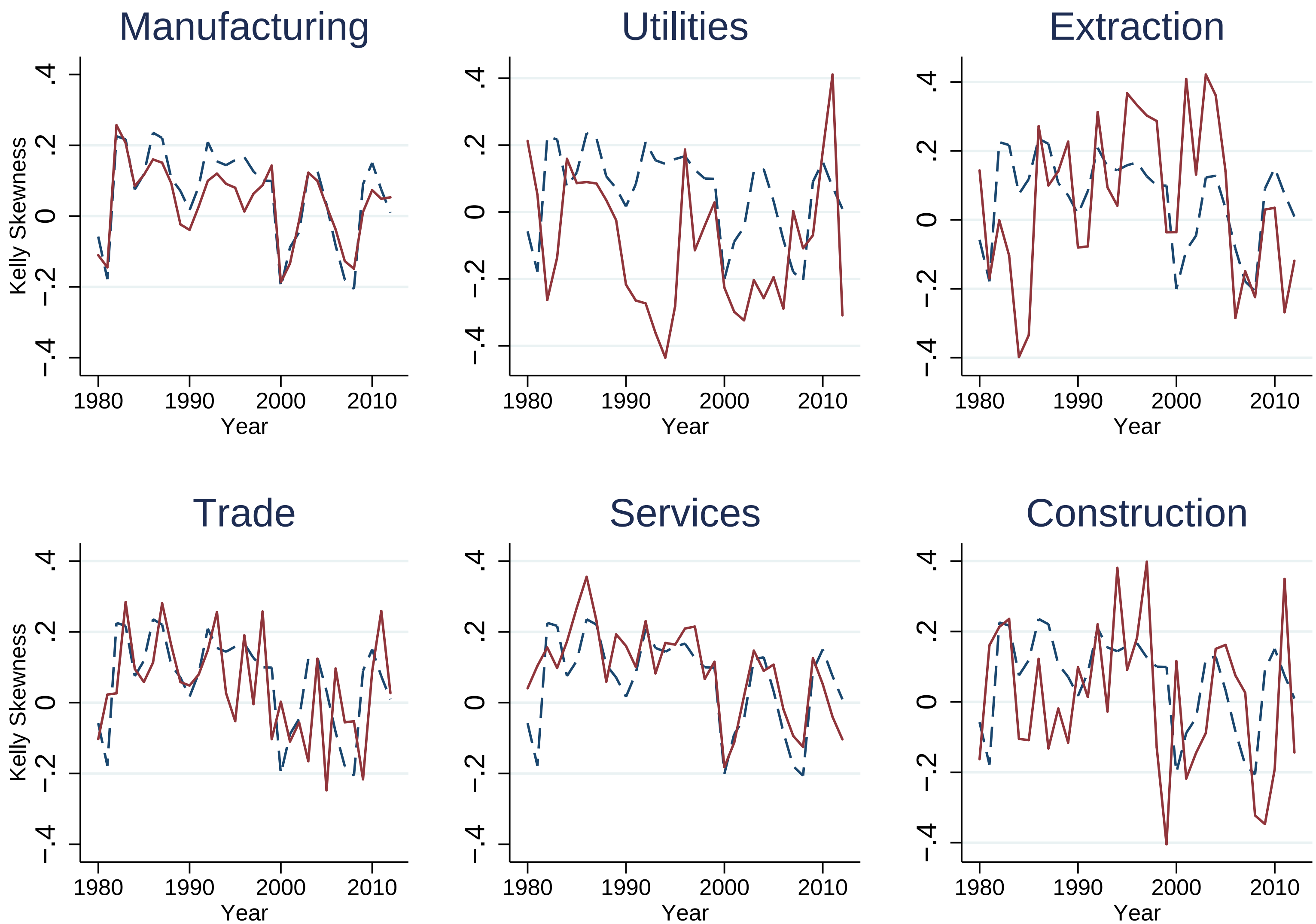

FIGURE 29 – Osiris: Skewness and GDP Growth

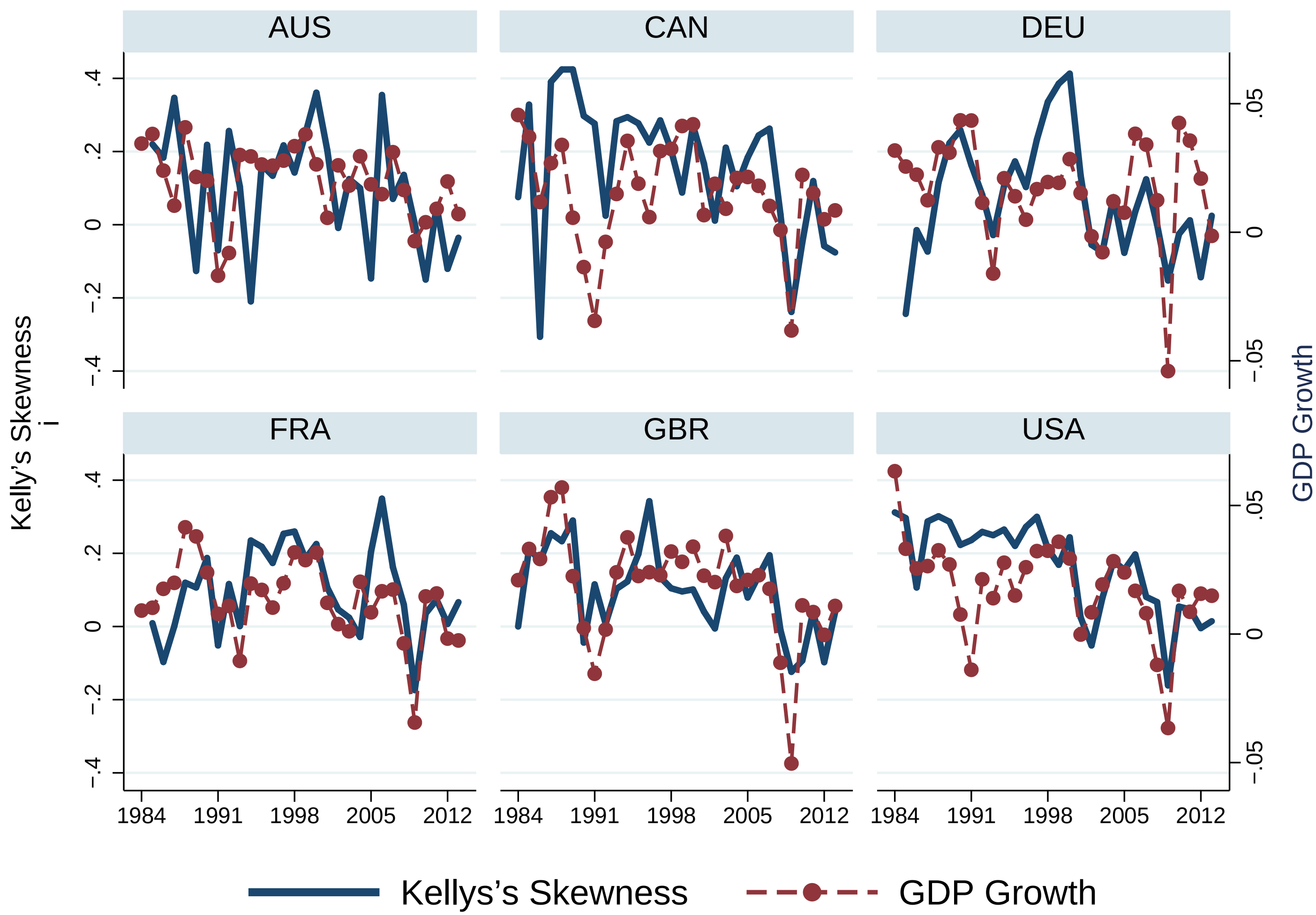

Figure 30 – Osiris: Skewness and GDP Growth

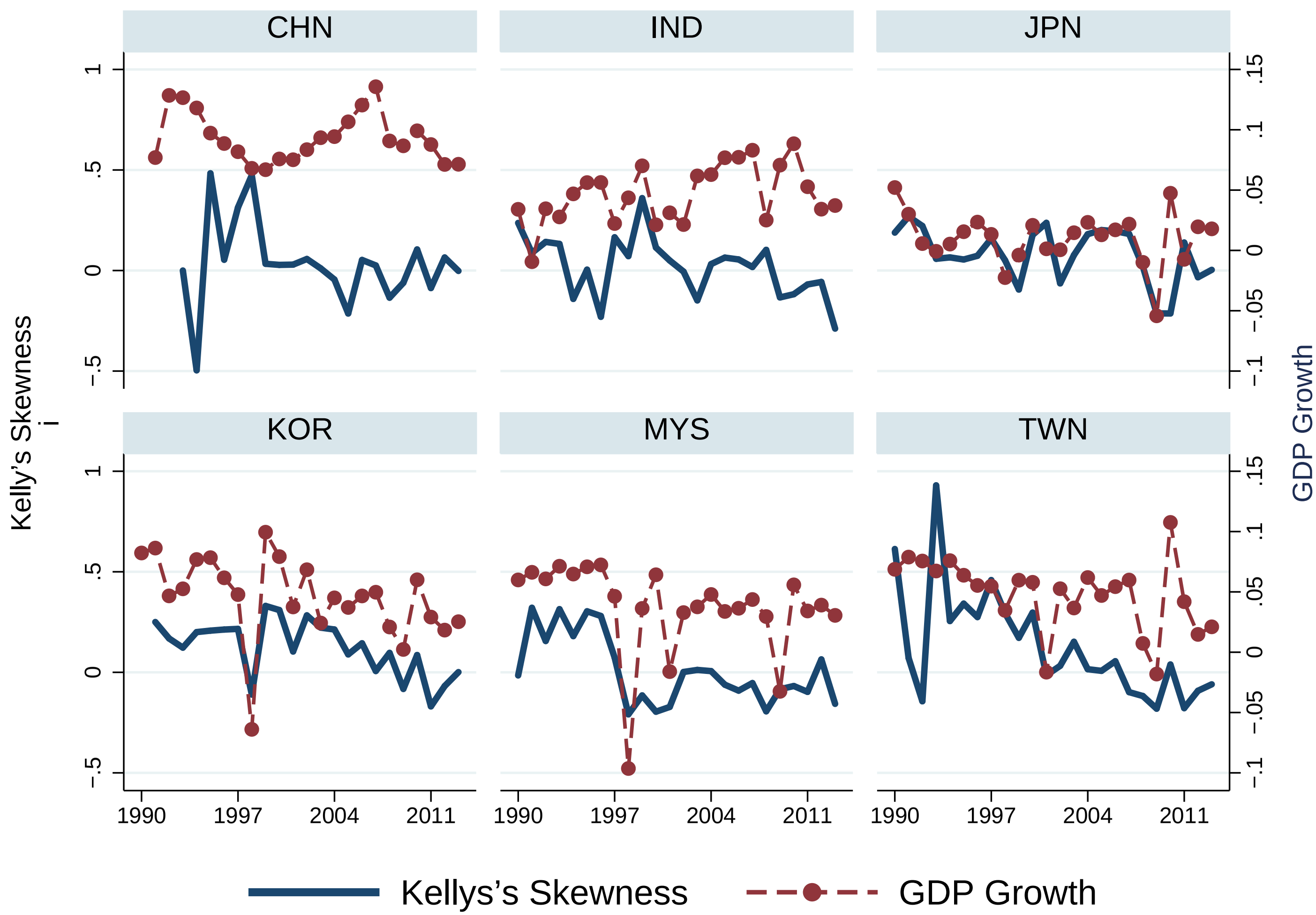

Figure 31 – Osiris: Dispersion and GDP Growth

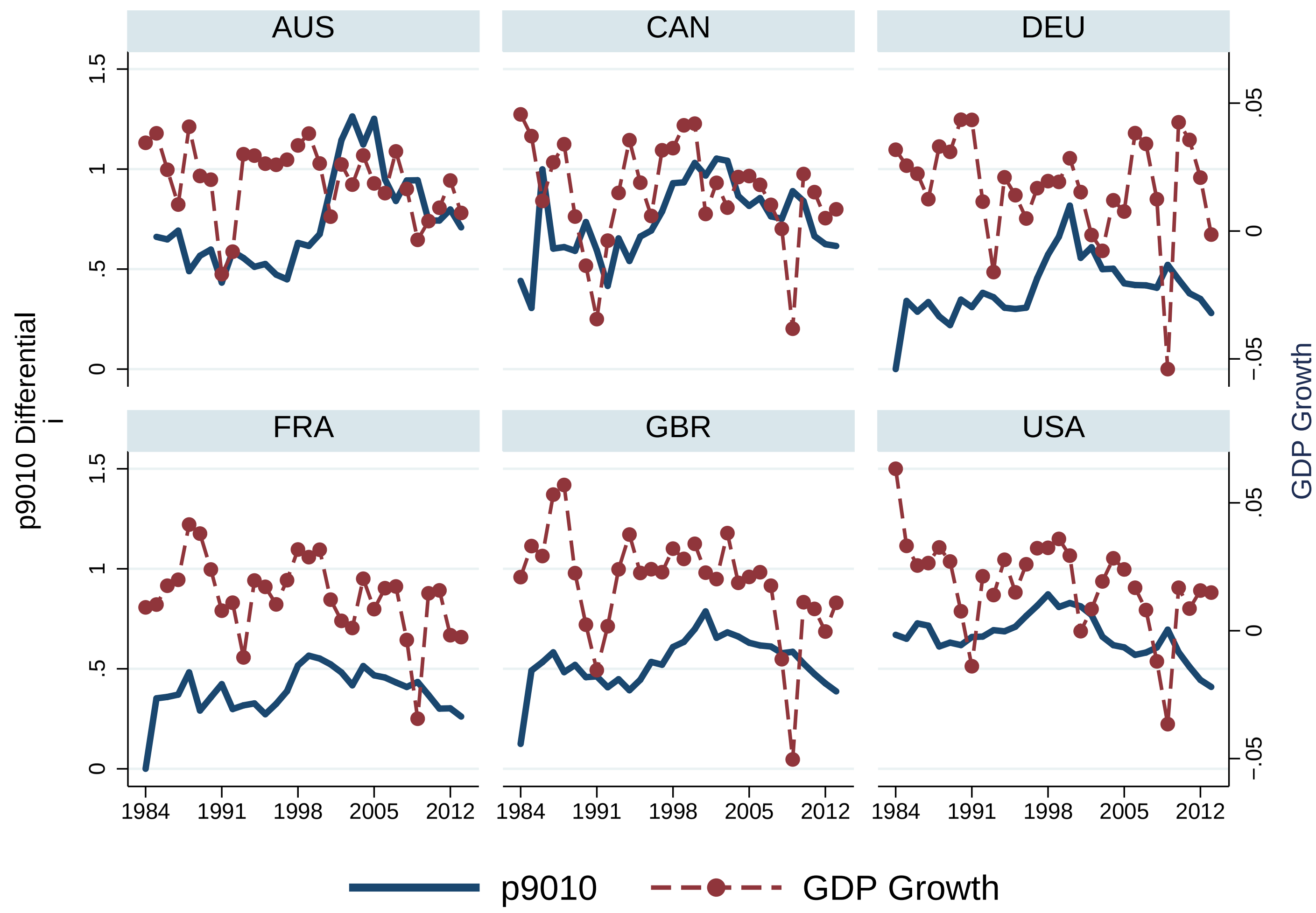

Figure 32 – Osiris: Dispersion and GDP Growth

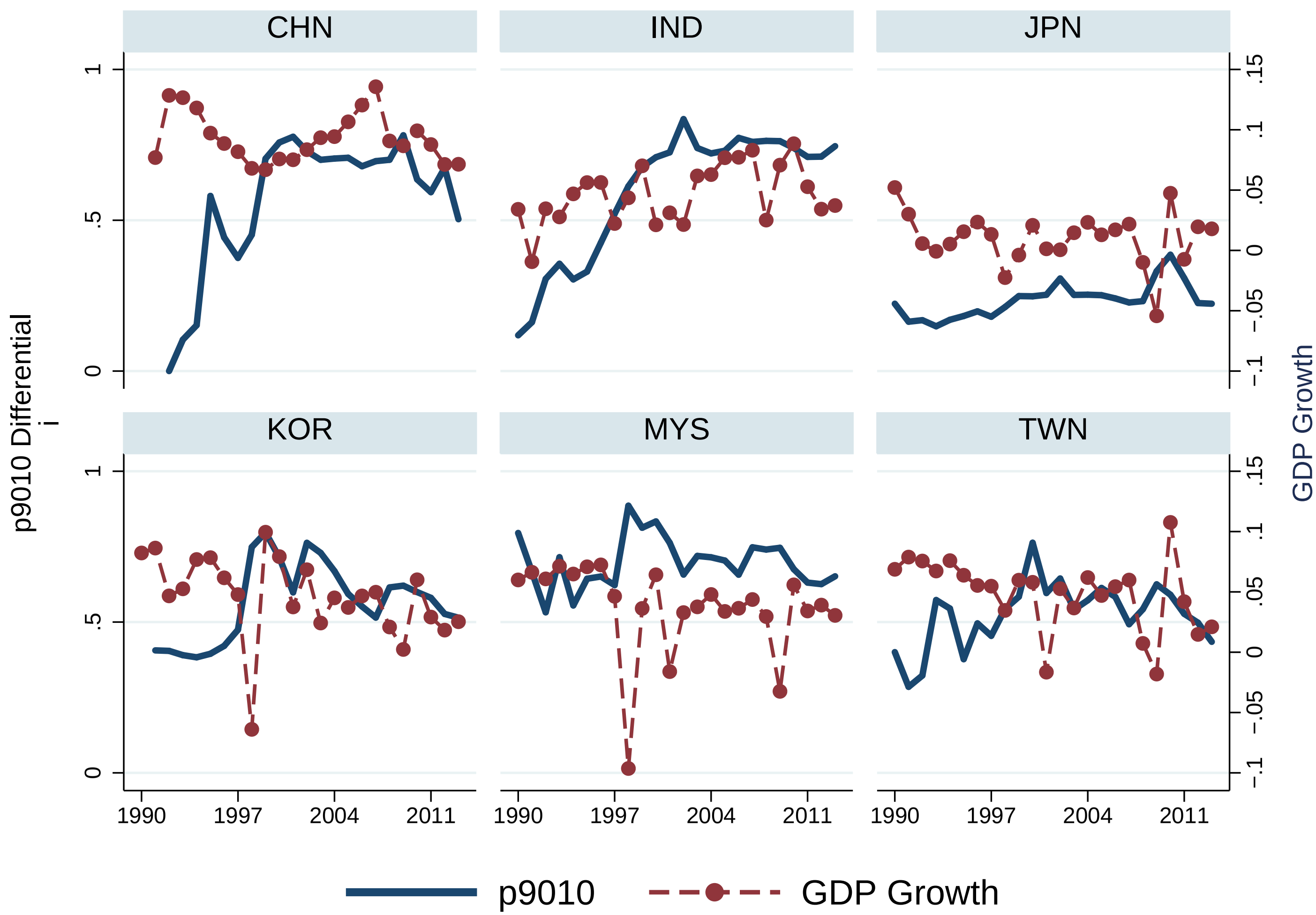

Figure 33 – Osiris: Upper and Lower Dispersion

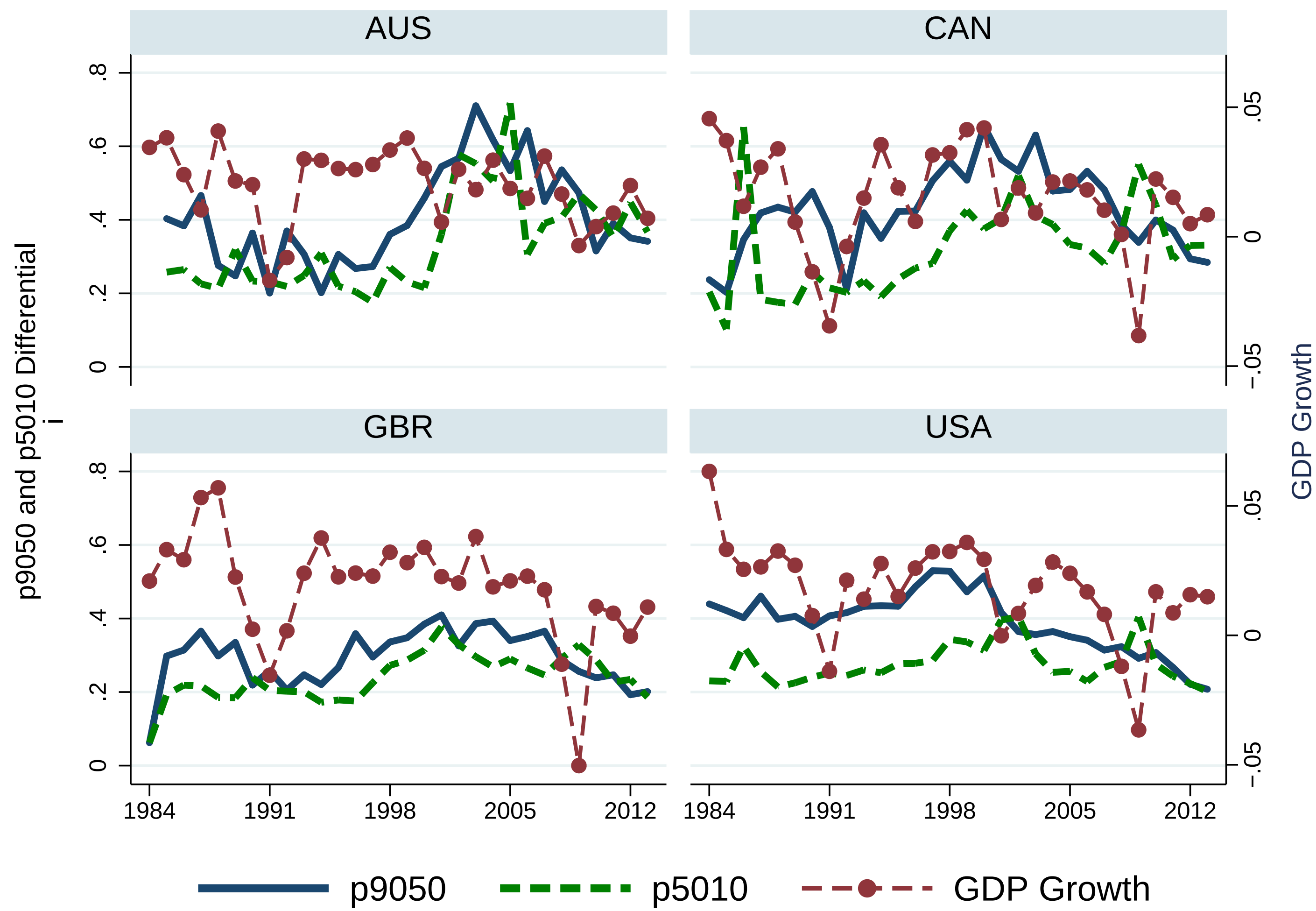

Figure 34 – Osiris: Upper and Lower Dispersion

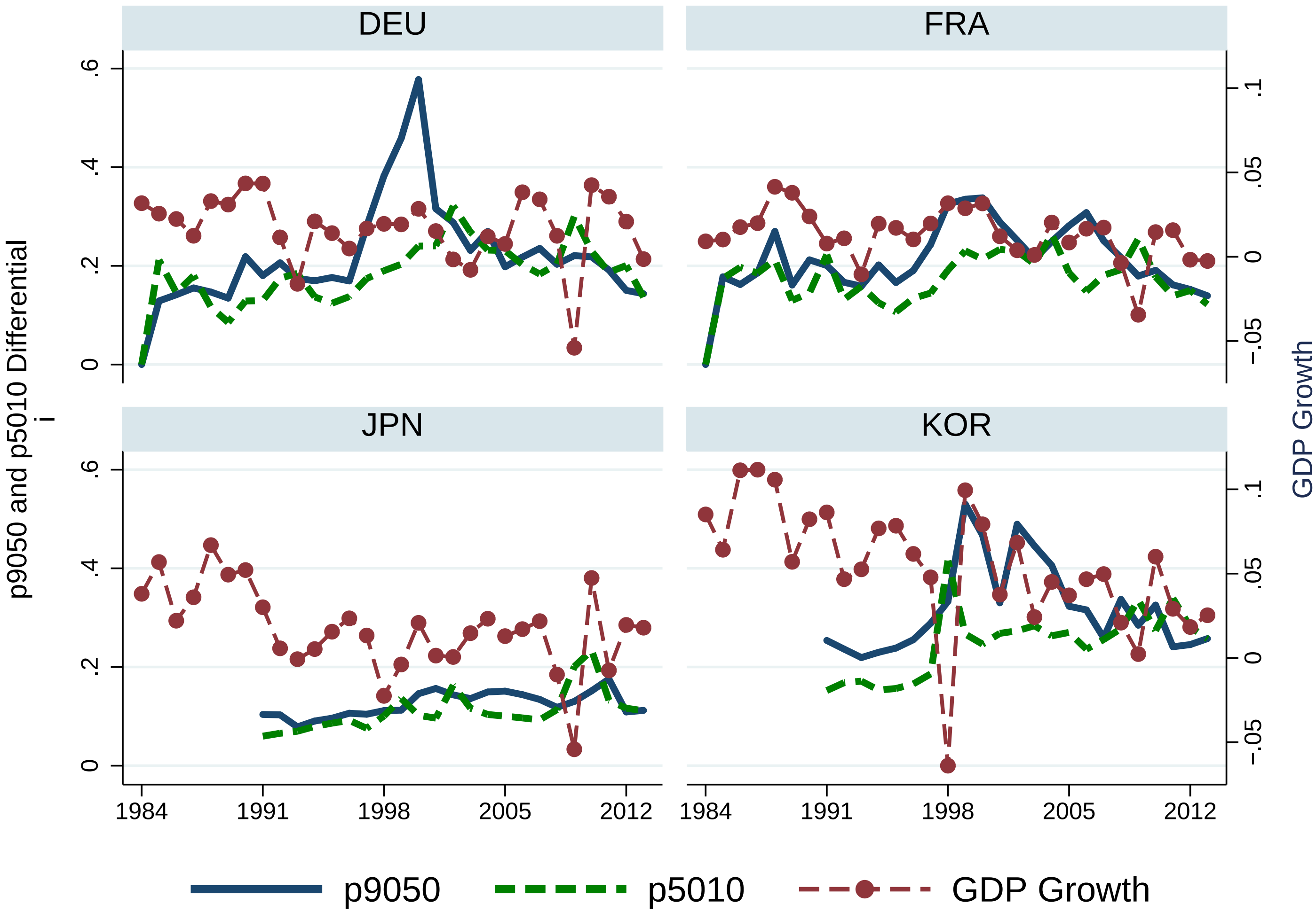

Figure 35 – Osiris: Upper and Lower Dispersion

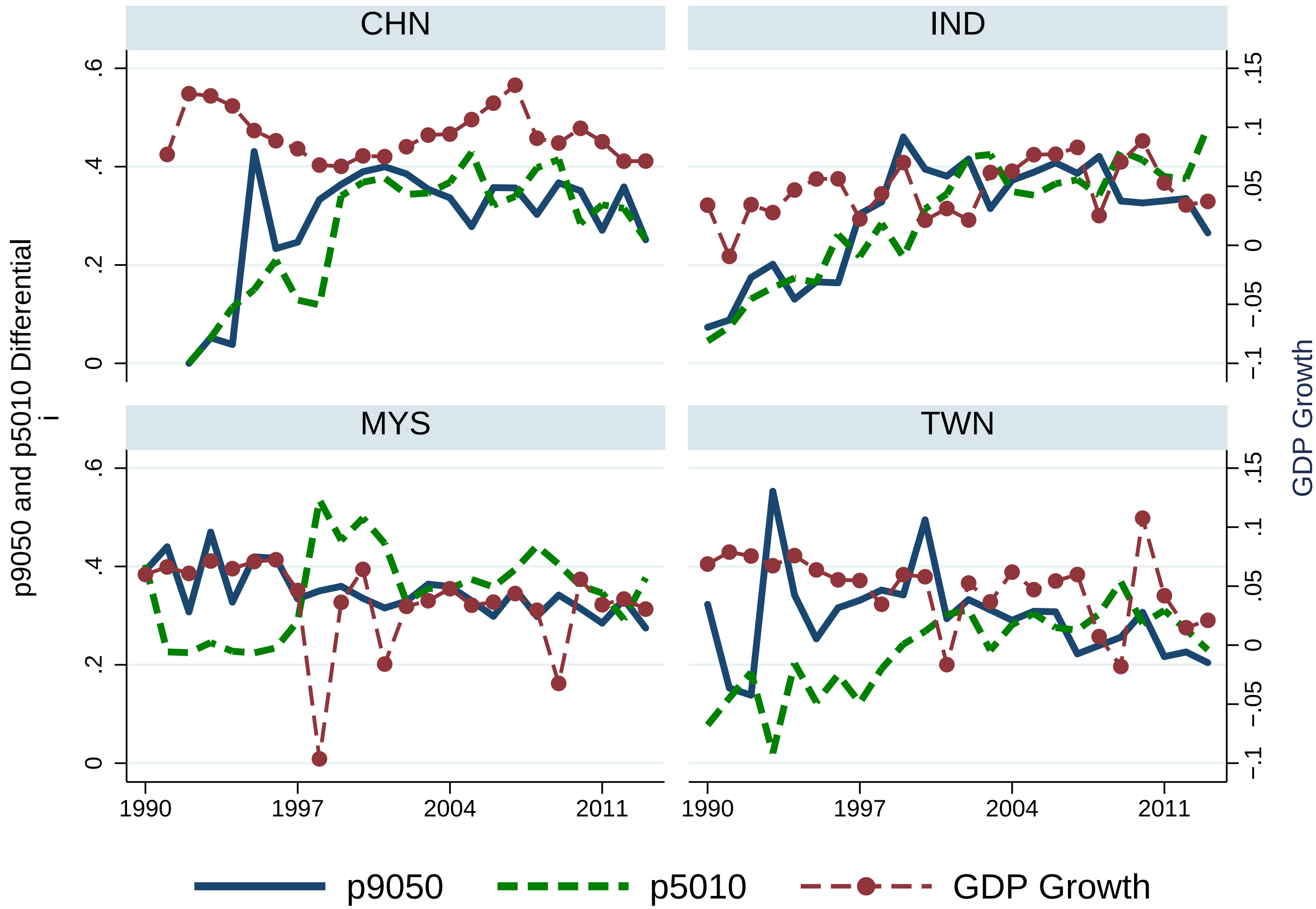

Figure 36 – Osiris: Cross Sectional Moments - European Union

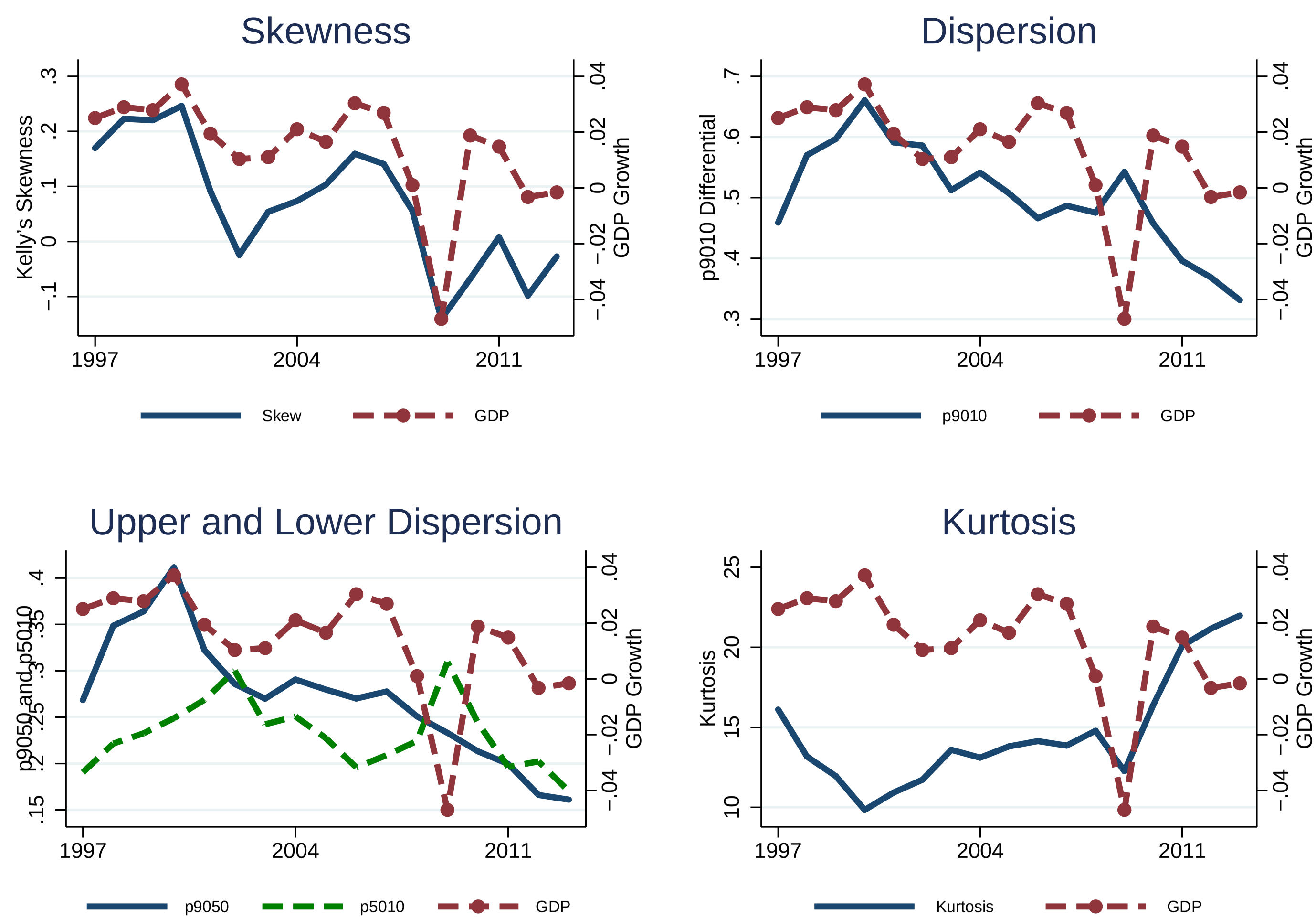

Figure 37 – Compustat Global: Skewness - Panel 1

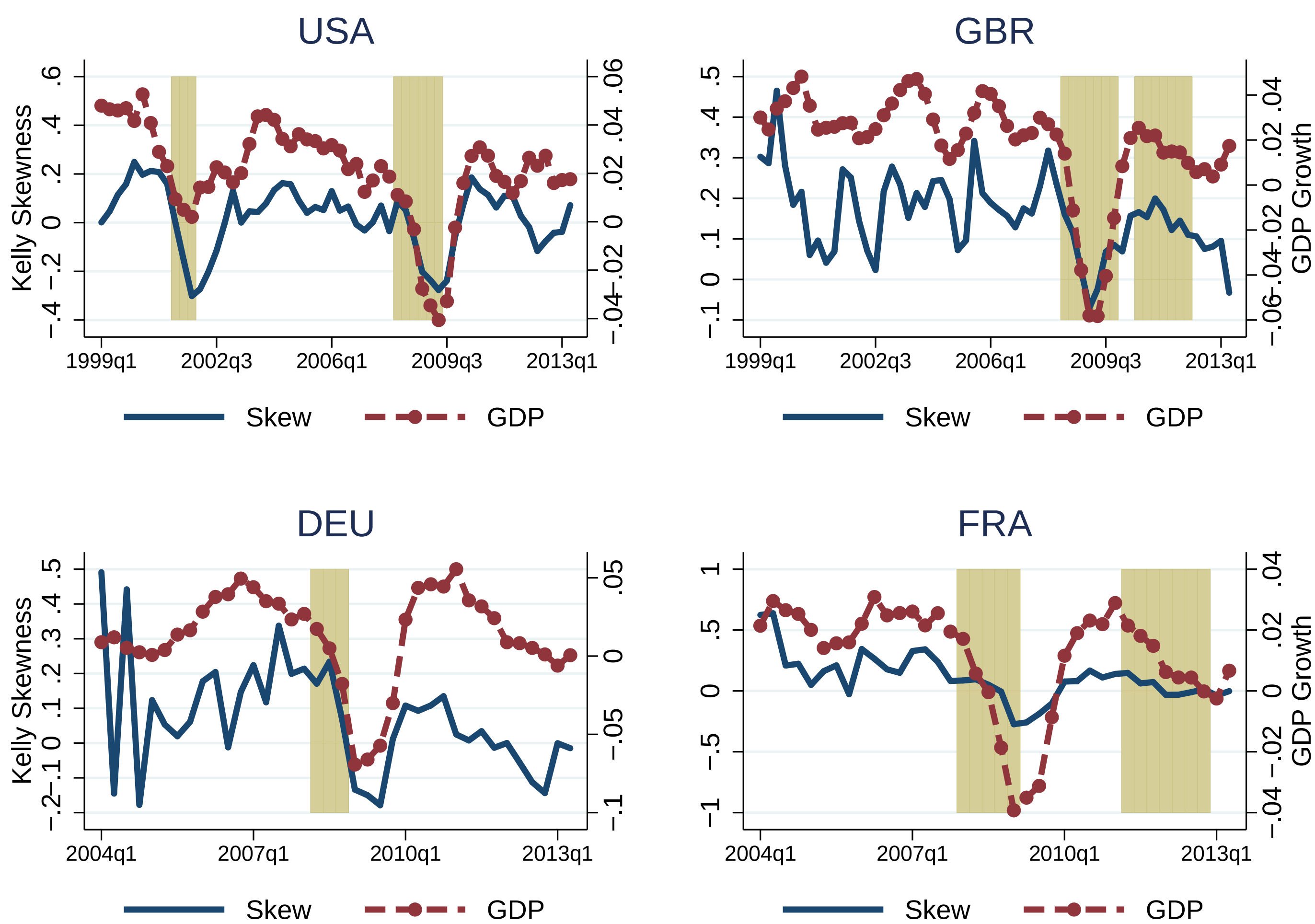

FIGURE 38 – Compustat Global: Skewness - Panel 2

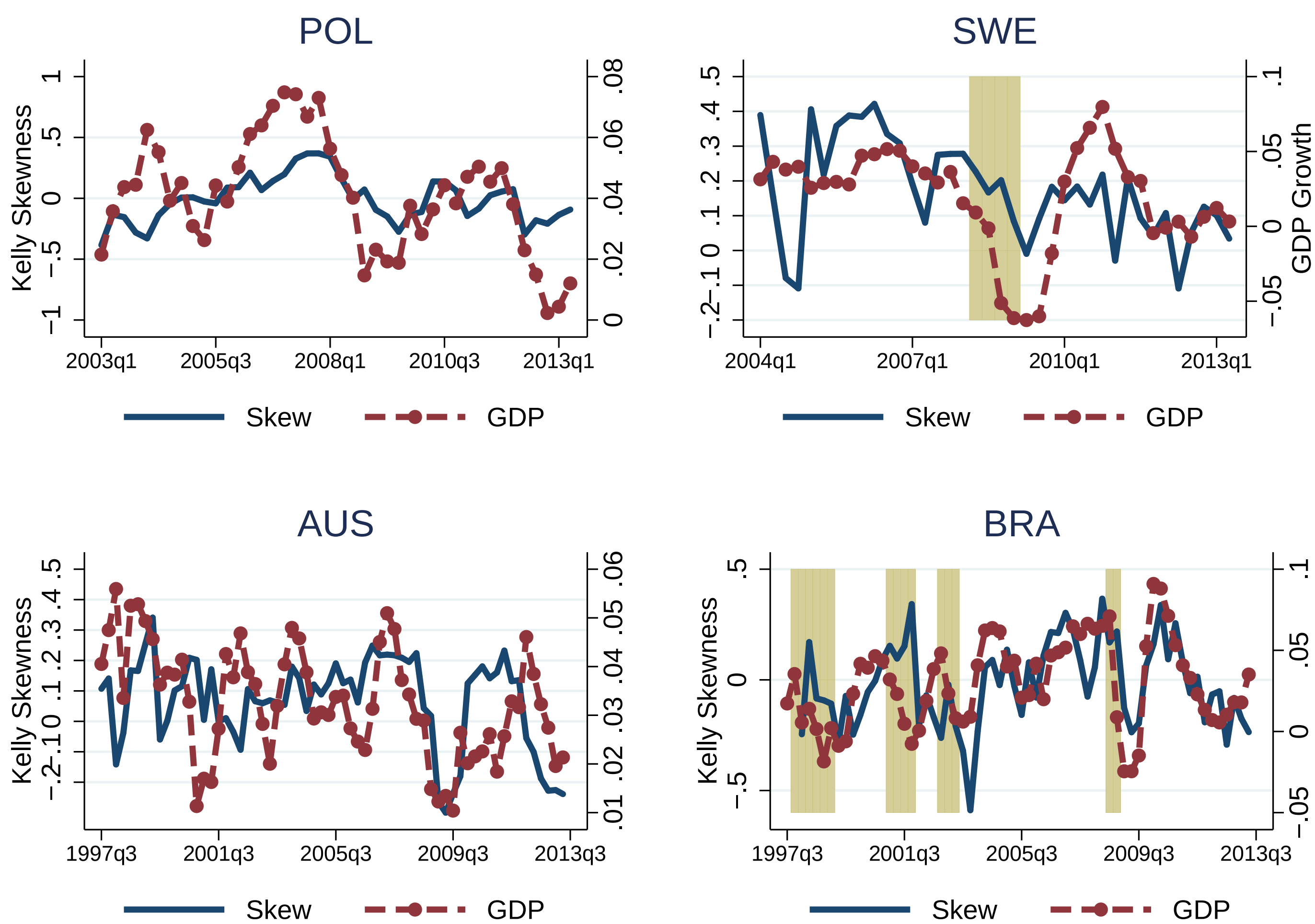

FIGURE 39 – Compustat Global: Skewness - Panel 1

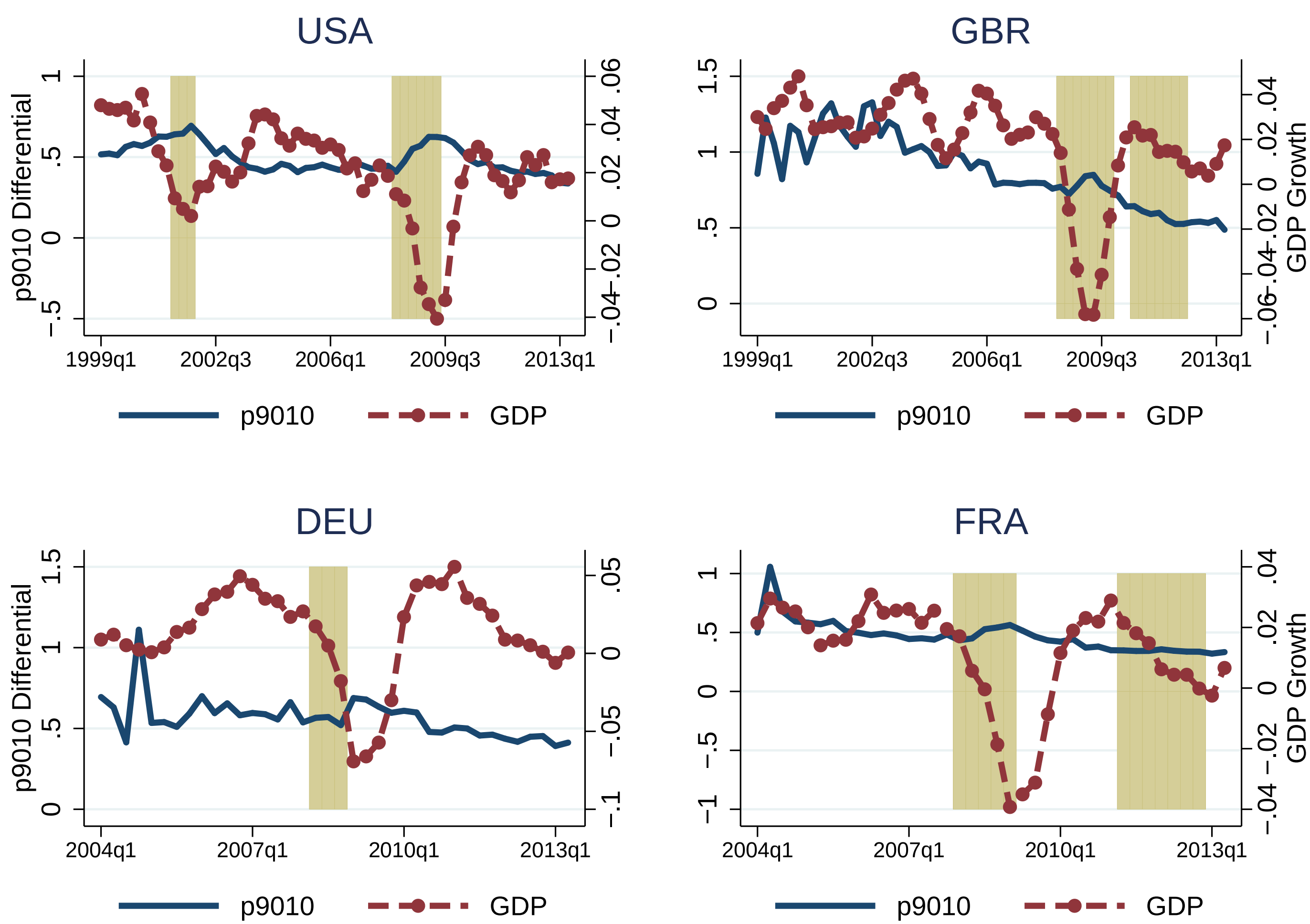

Figure 40 – Compustat Global: Dispersion - Panel 2

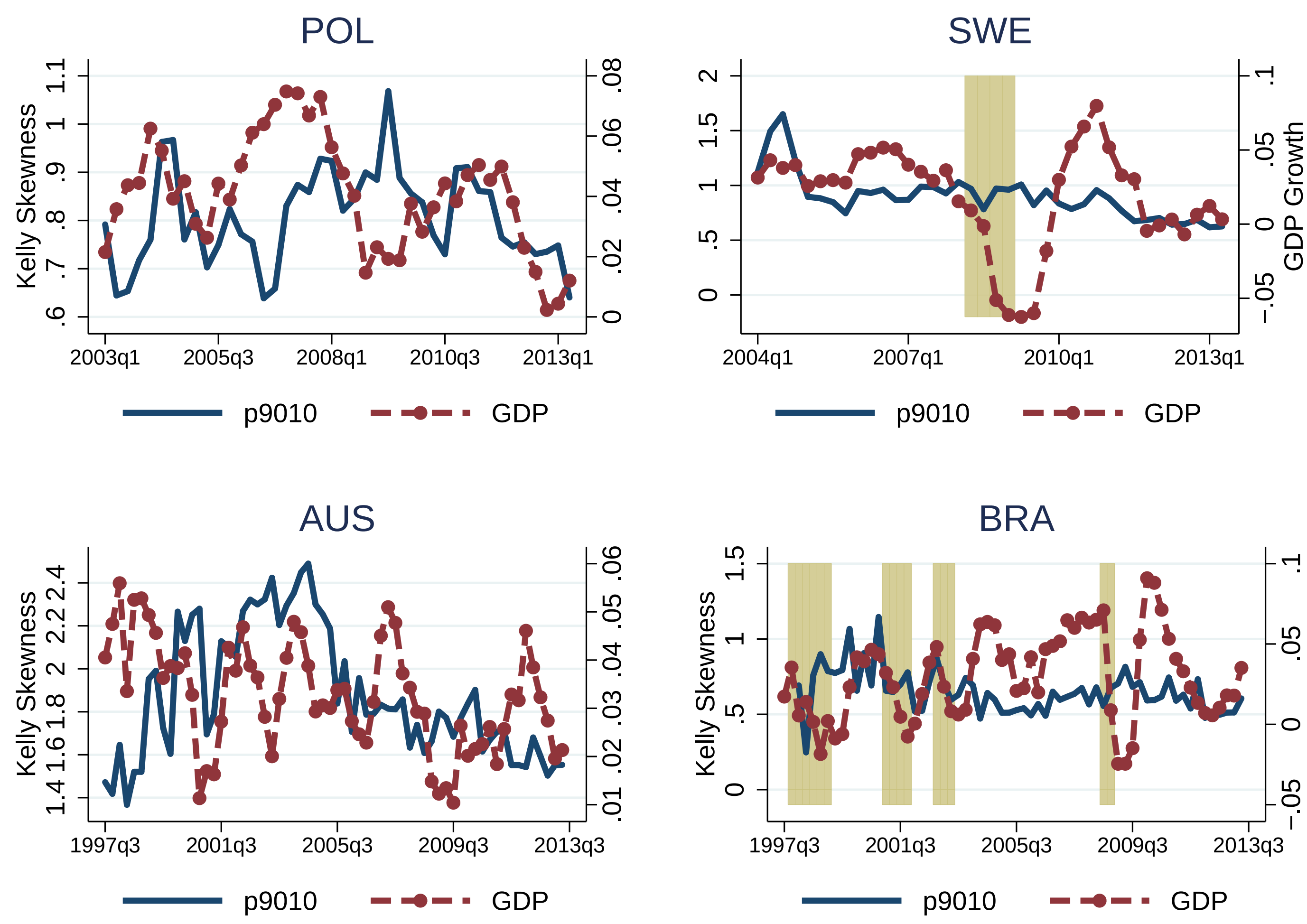

FIGURE 41 – Compustat Global: Cross Sectional Moments - European Firms

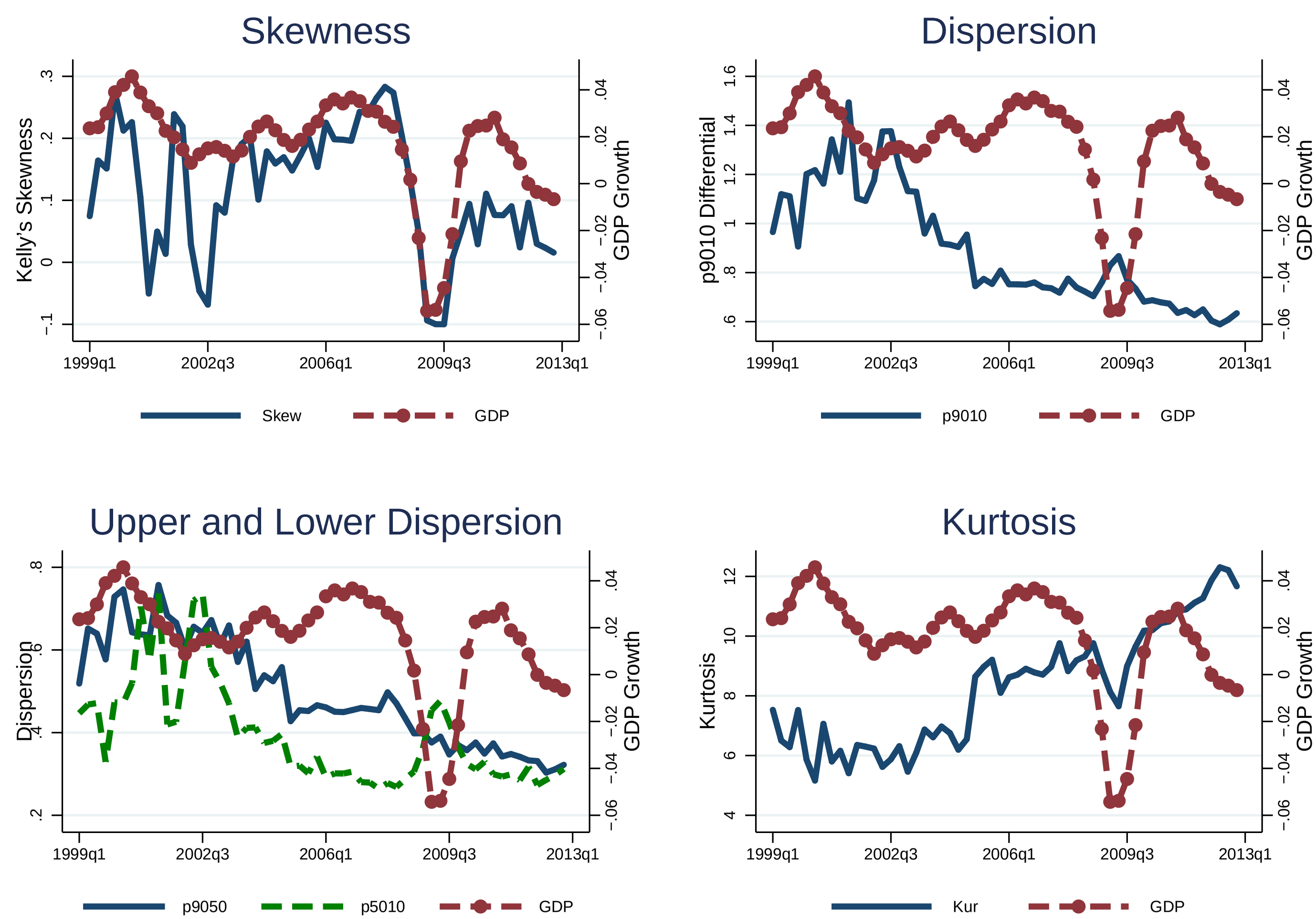

Figure 42 – Compustat Global: Distribution of Sales Growth Rates: Peak and Trough of the Great Recession

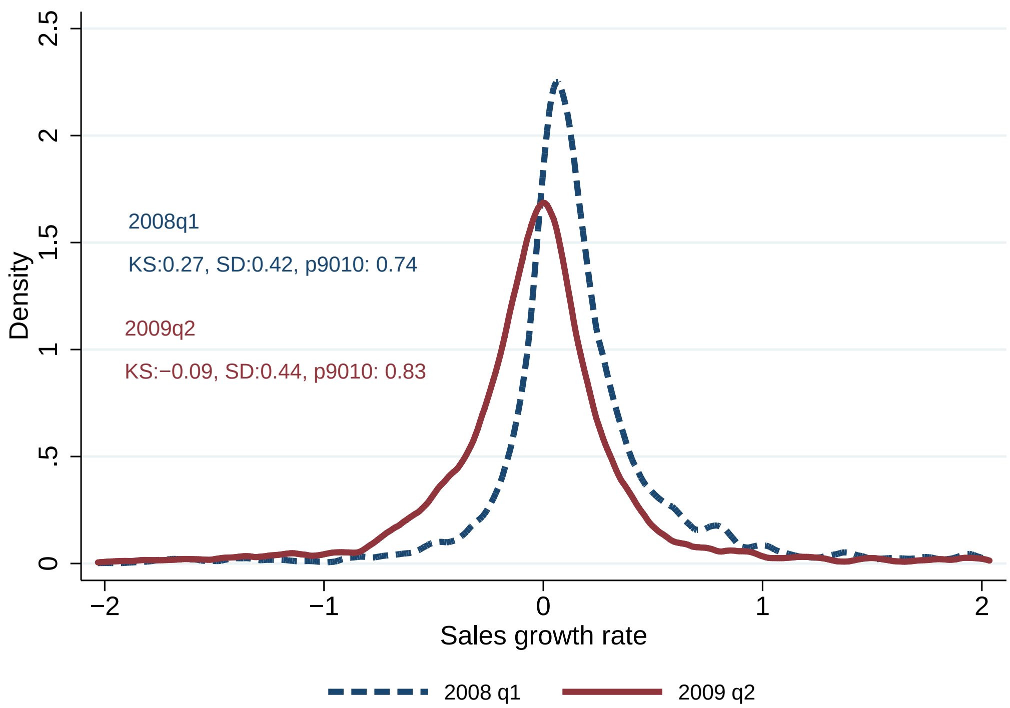

Figure 43 – Compustat Global: Distribution of Sales Growth Rates: Years Before and During of the Great Recession

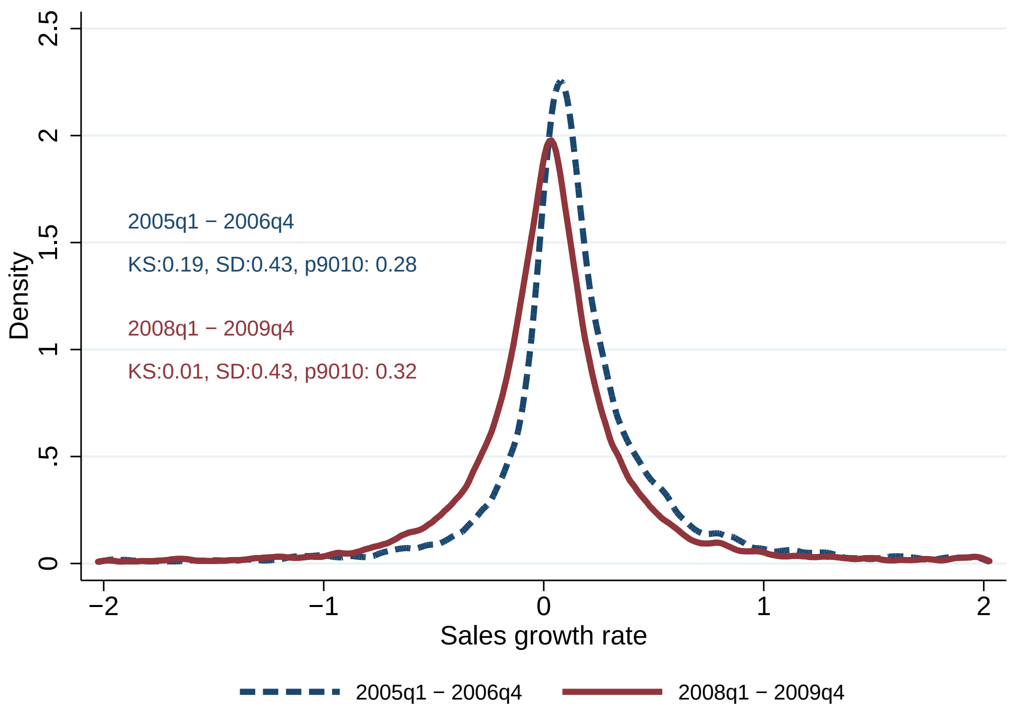

Figure 44 – Orbis: Skewness and GDP Growth - Set 1

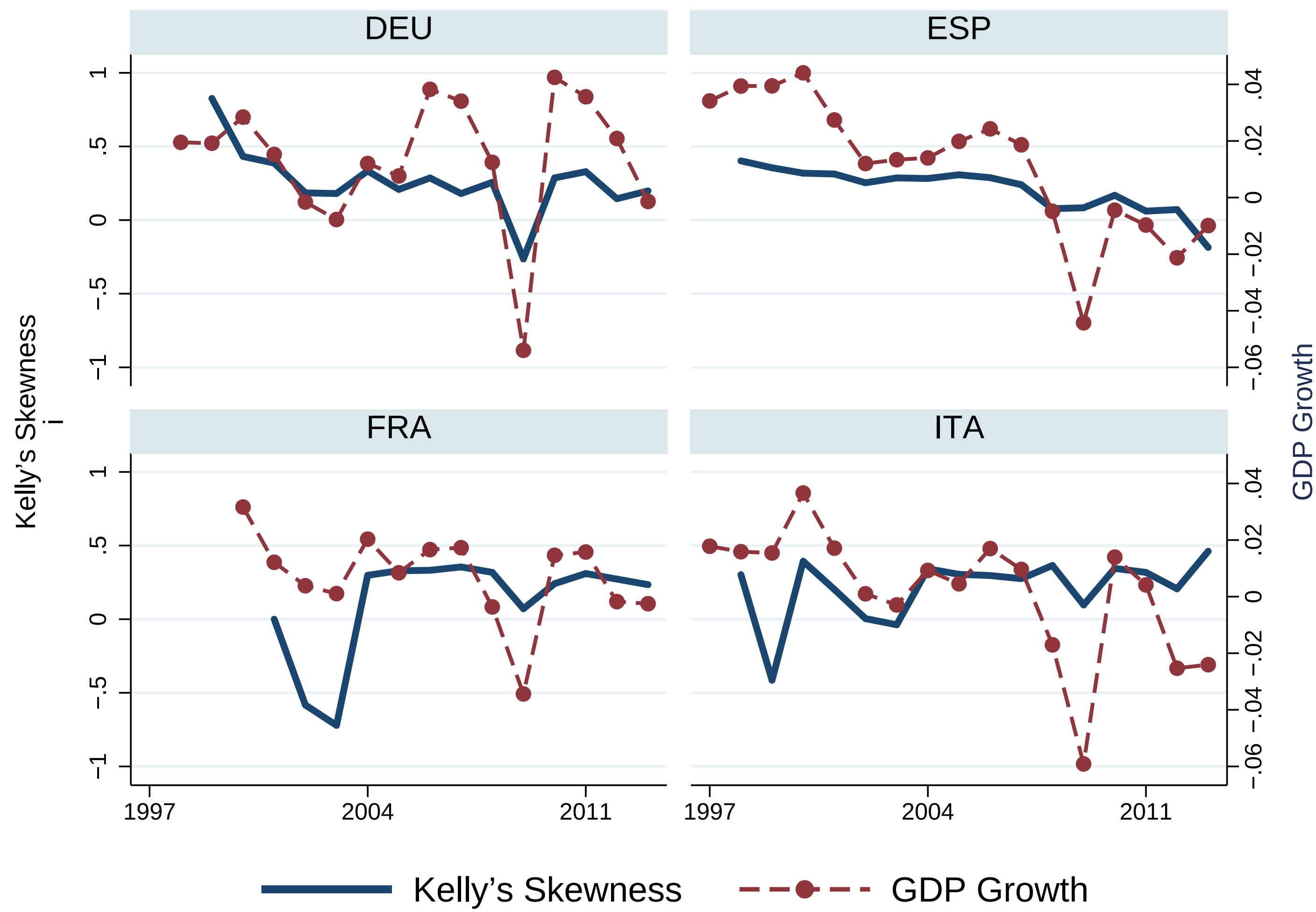

FIGURE 45 – Orbis: Skewness and GDP Growth - Set 2

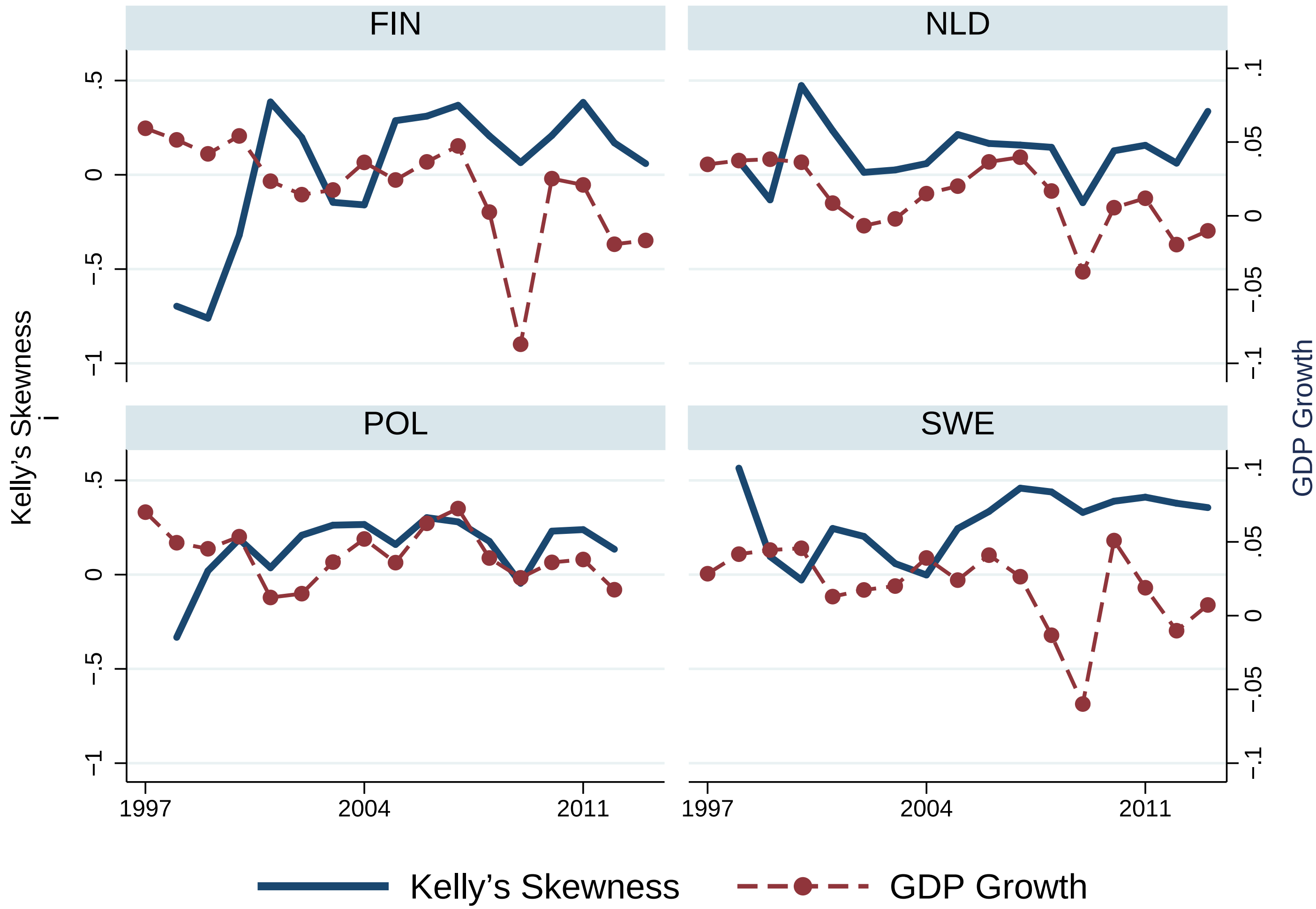

Figure 46 – Orbis: Dispersion and GDP Growth - Set 1

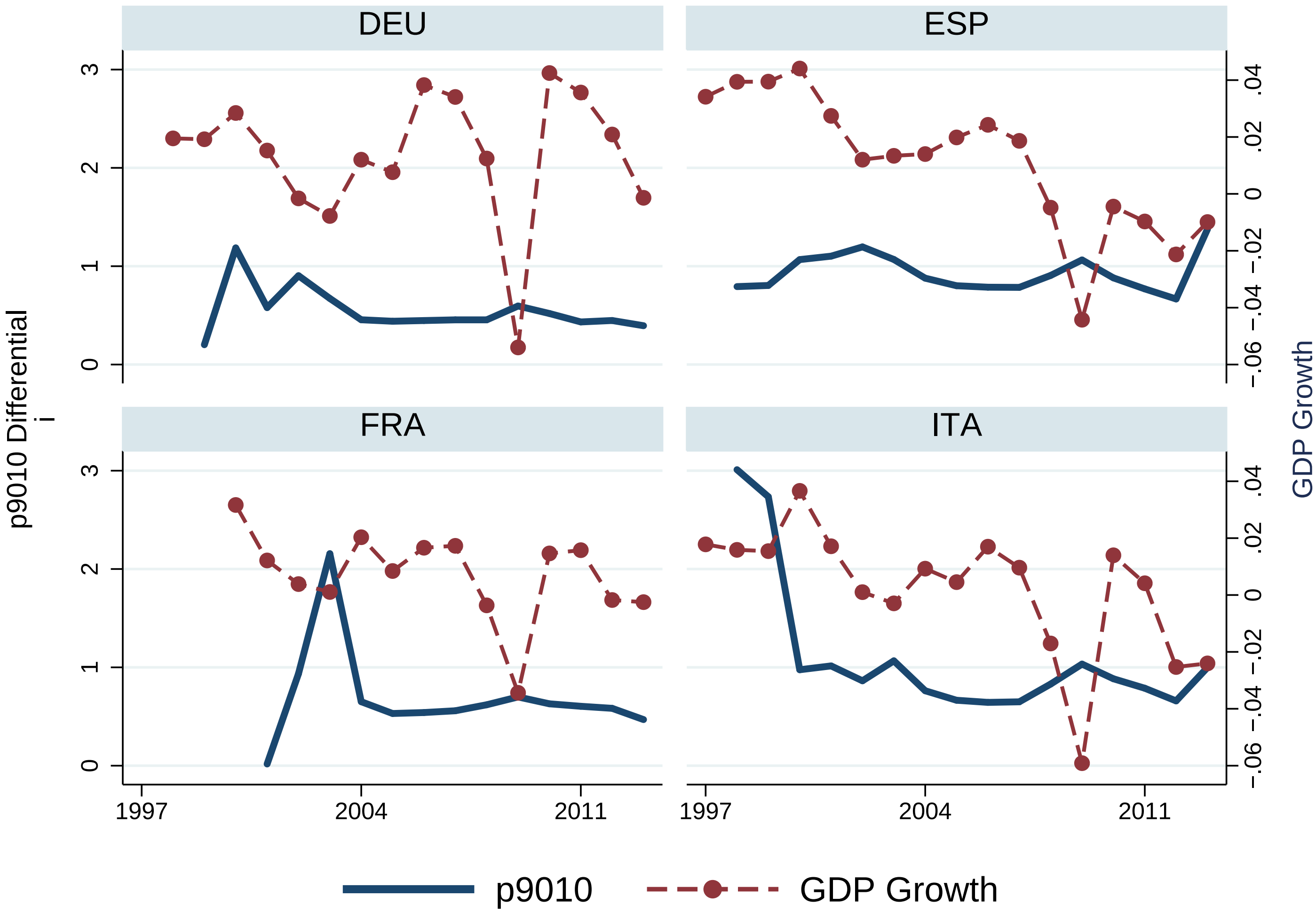

FIGURE 47 – Orbis: Dispersion and GDP Growth - Set 2

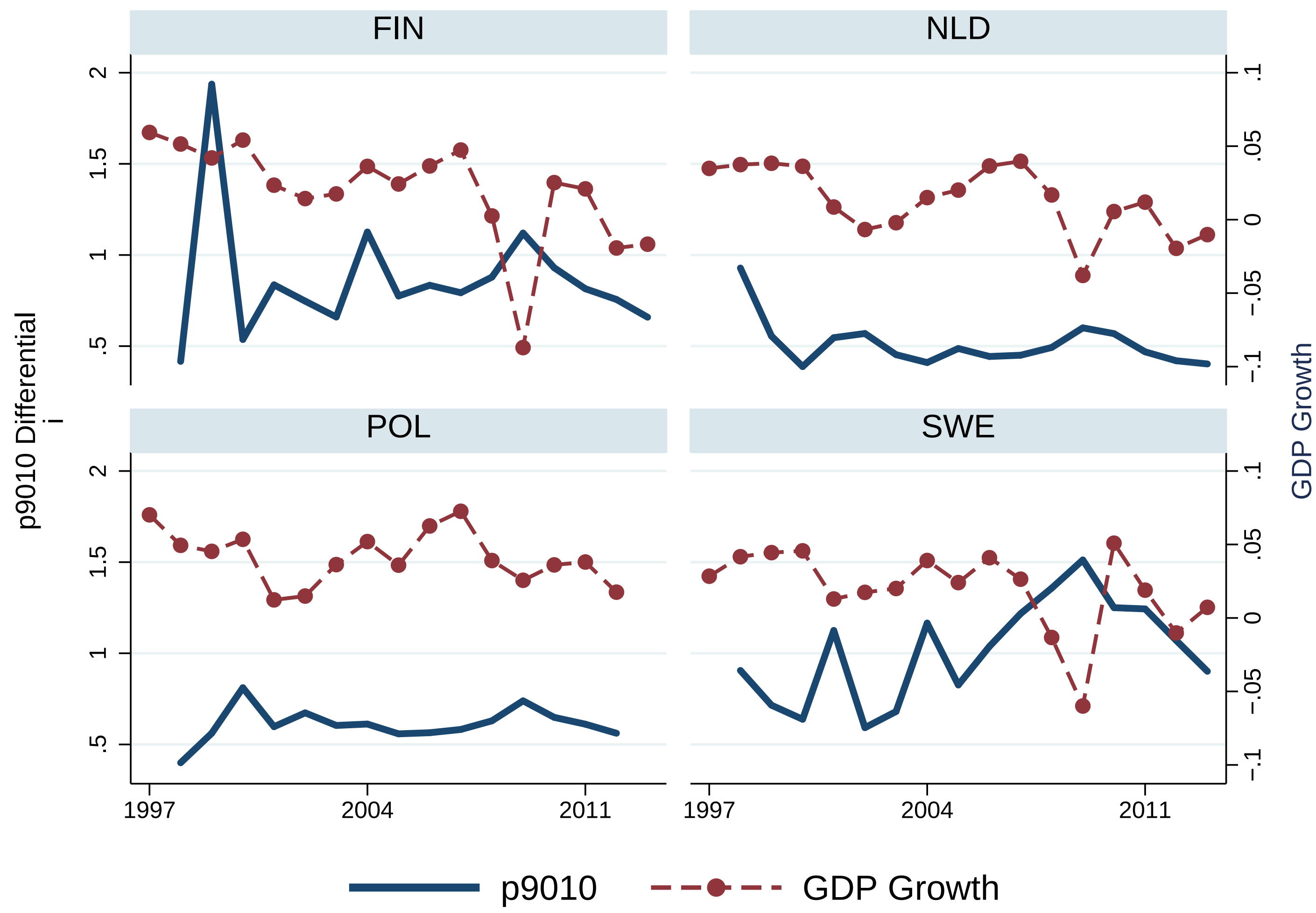

Figure 48 – Orbis: Upper and Lower Dispersion and GDP Growth - Set 1

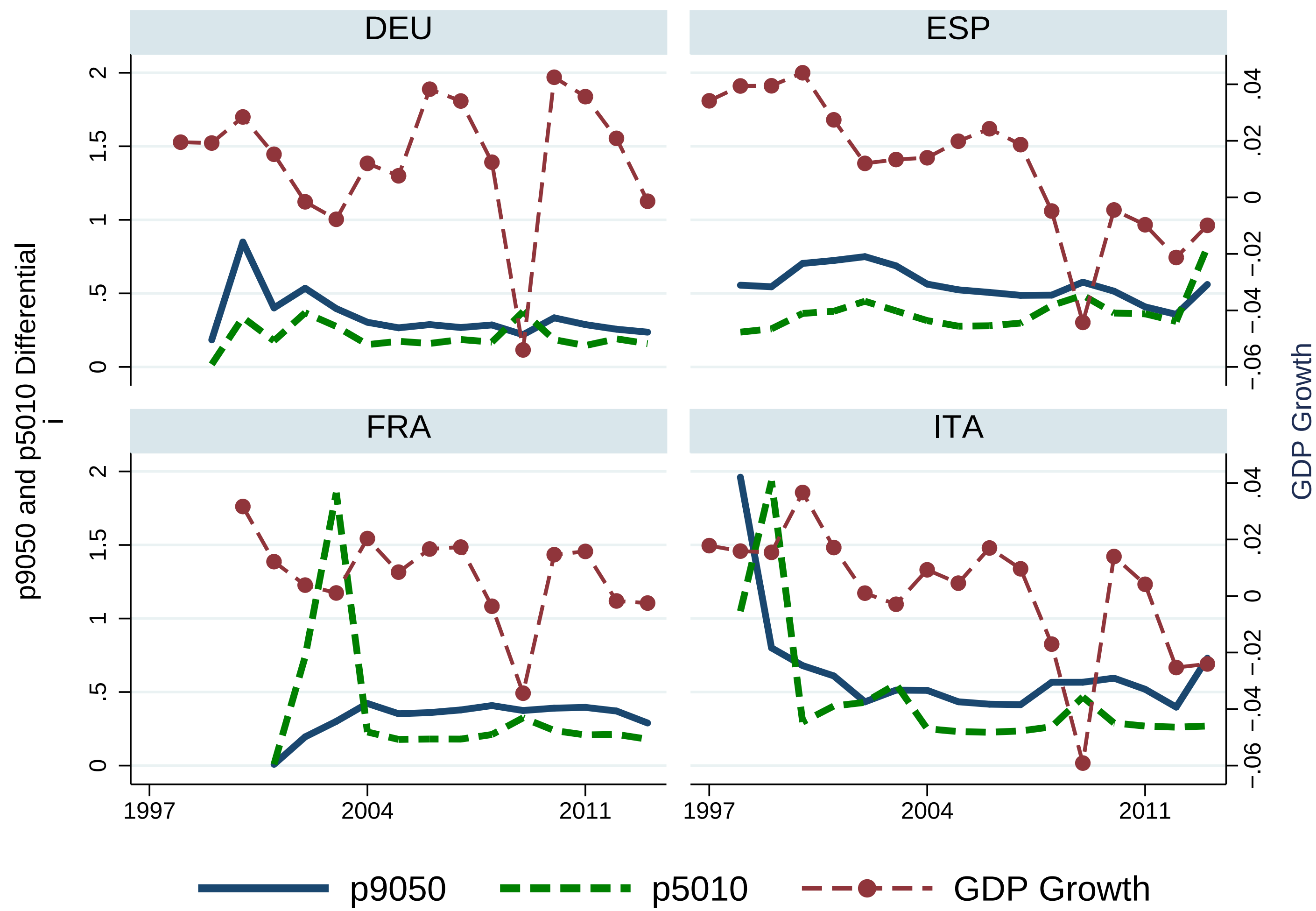

FIGURE 49 – Orbis: Upper and Lower Dispersion and GDP Growth - Set 2

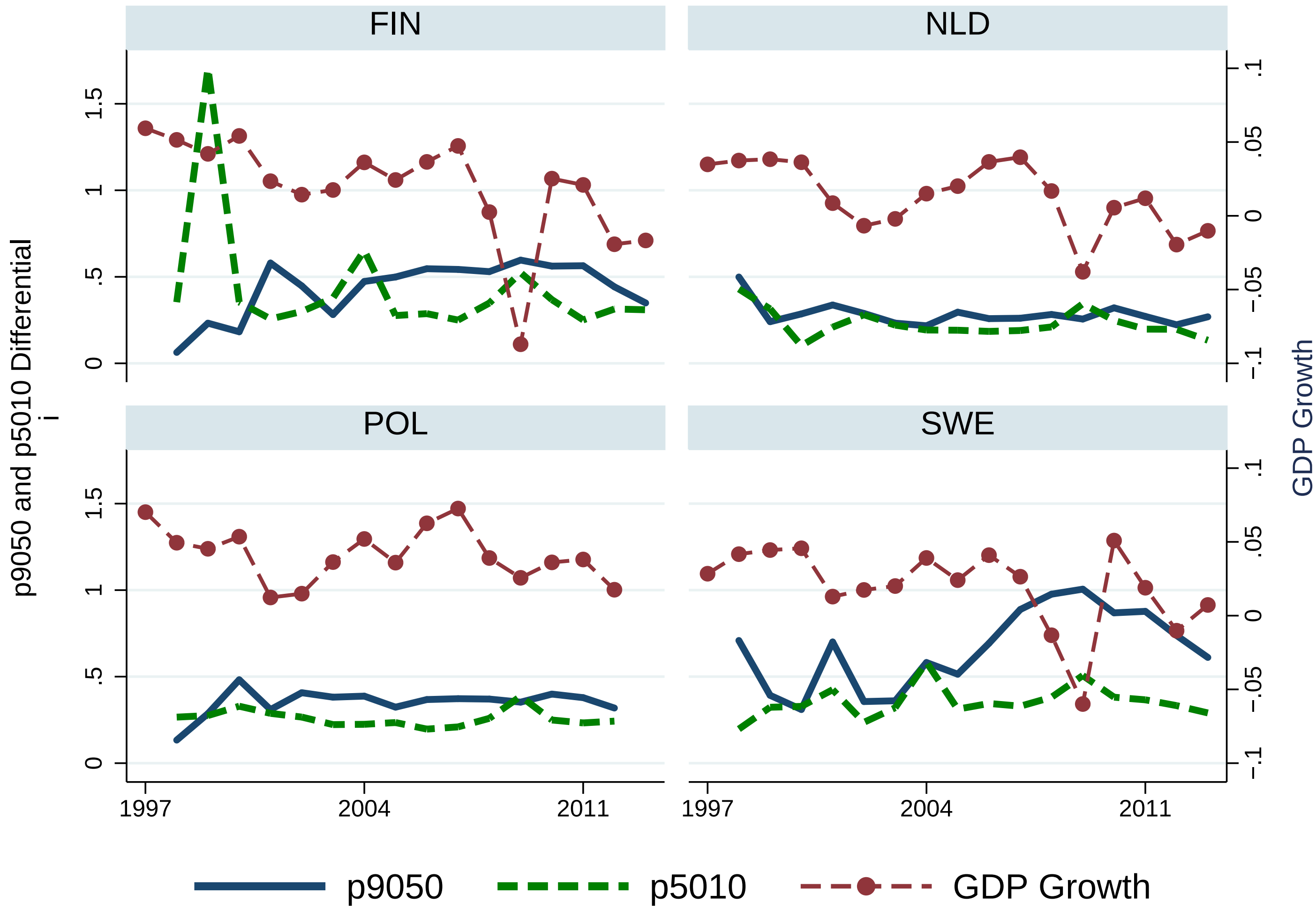

FIGURE 50 – Orbis: Cross Sectional Moment of European Firms

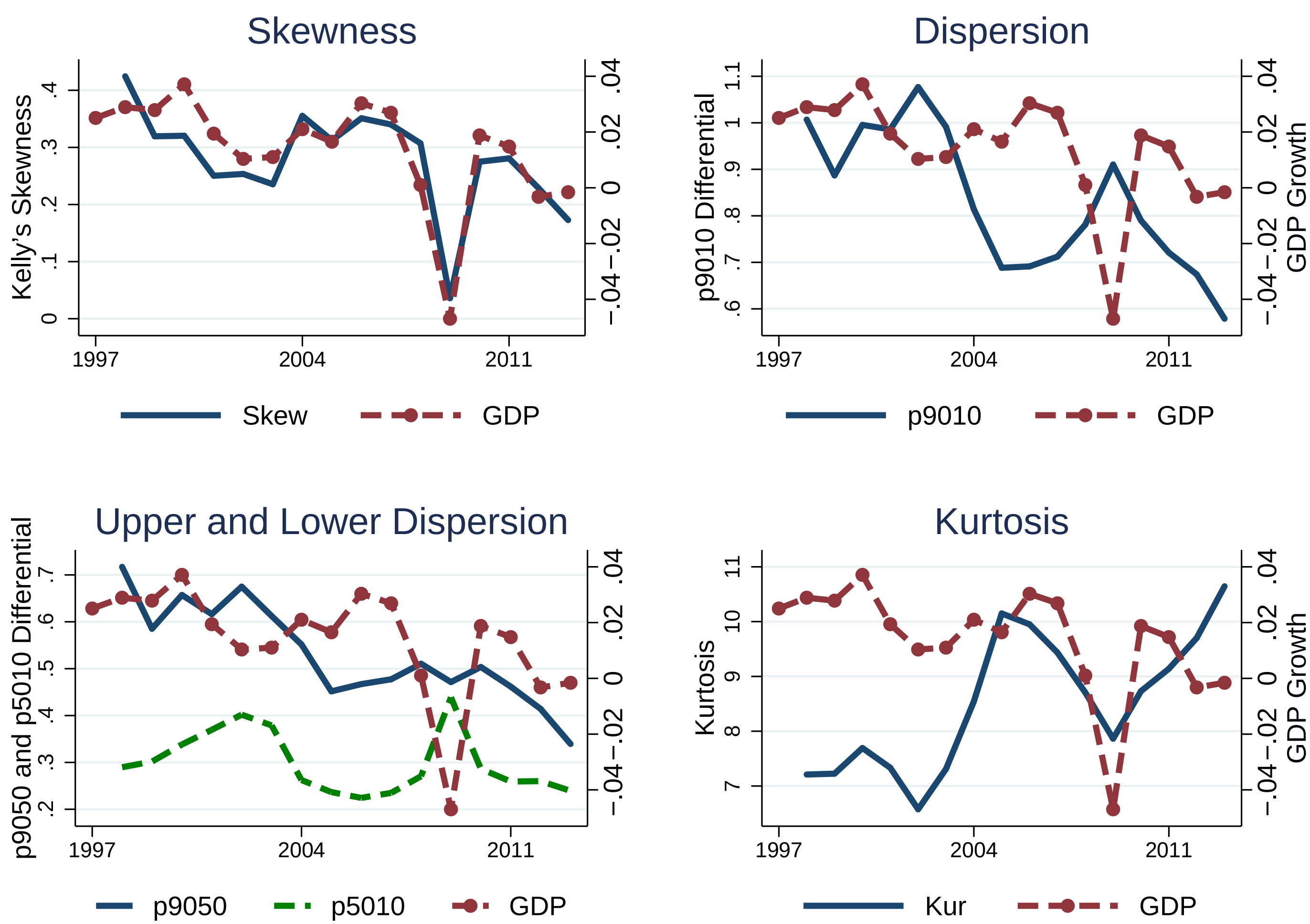

Figure 51 – Orbis: Distribution of Sales Growth Rates: Years Before and During of the Great Recession

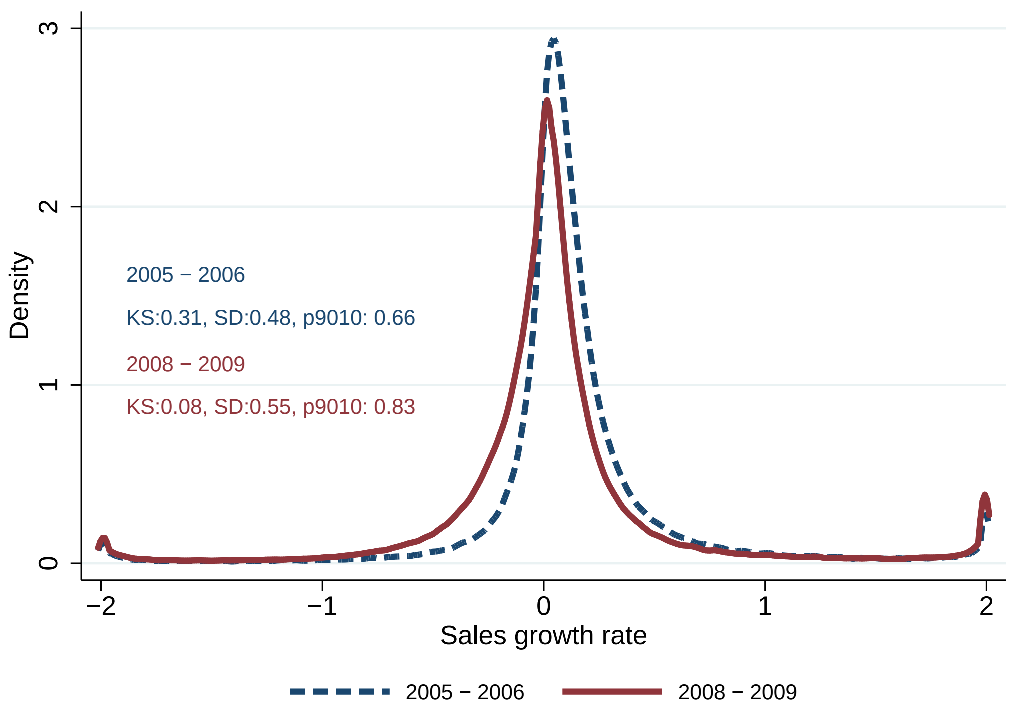

Figure 52 – Orbis: Cross Sectional Moment of European Firms