Skewed Business Cycles

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Preliminary and Incomplete. Comments Welcome.

Abstract

This paper studies how the distribution of the growth rate of firm-level variables (sales, profit, inventories, and employment) changes over the business cycle. Using a panel of Compustat firms from 1964 to 2013 we find that, in addition to the well-documented counter cyclicality in dispersion, 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 counter cyclicality of dispersion. These results are robust to different selection criteria, across firm size categories, and across industries. We also analyze the distribution of macroeconomic outcomes such as GDP growth and stock returns using a panel of developed and developing countries. Here we also find evidence of declining skewness during periods of low economic activity.

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1 Introduction

This paper studies how the distribution of the growth rates of firm-level variables (sales, profit, inventories, and employment) change over the business cycle. 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, the solid line of figure 1 shows the density of firm-level growth rates of sales between 2007Q1 and 2008Q1—just before the Great Recession—while the dashed line is the density for the same variable between 2008Q1 to 2009Q1—leading up the trough of the recession. From left to right, the bars are the 10th and the 90th percentile of each distribution.

In the figure, the difference between the 90th and 10th percentiles increases from 0.41 to 0.64. At the same time, a robust measure of skewness—Kelly's skewness—declines 0.10 to –0.25. 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 0.07 in 2006–2007 means that approximately, the P9050 accounts for 55% of overall dispersion (P9010), whereas the lower tail, P5010, accounts for the remaining 45%. The figure of –0.26 in the Great Recession means that the upper tail accounts for only 37% of P9010 and the lower tail accounts for 63%. 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 quarters, 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. growth of the GDP per capita and employment growth). Additionally, we find that most of the increase of

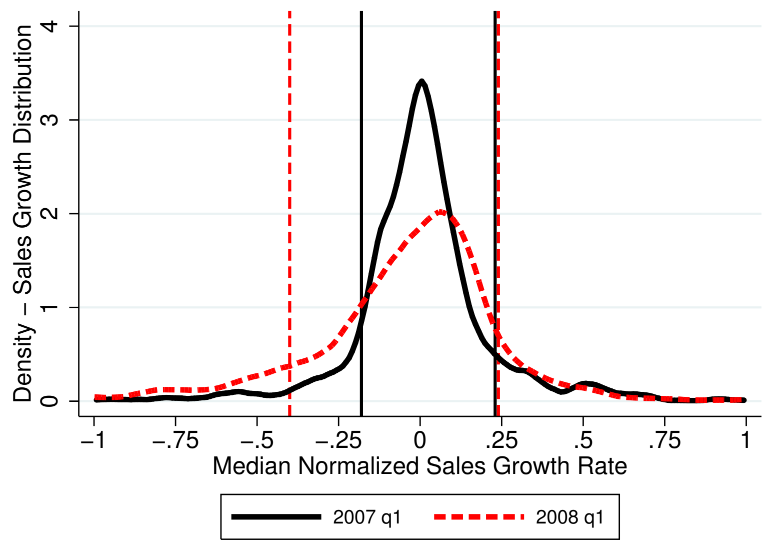


FIGURE 1 – The histogram for each time period is constructed using the arc-percent change between quarter t and $t+4$. The arc-percent change is defined as $g_{i,t} = 2\left(x_{i,t+4} - x_{i,t}\right) / \left(x_{i,t} + x_{i,t+4}\right)$. Both distributions are adjusted to have the same median equal to 0.

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. We also study the cross sectional distribution of the growth rate of sales in a wide sample of European,Asian, and Latin American countries. Despite the large differences between data sets and countries, we find a robust positive relation between the 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.

We also study the cyclicality of skewness at macroeconomic level. For doing that we use a panel of developed and developing countries for which we calculate measures of dispersion and skewness of the GDP growth and daily returns of stock prices indexes. Using this panel of countries we find that skenwess of the growth rate of GDP and the stock returns decrease significantly during periods of low economic activity, in line with our results using firm level data.

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 additional incentives to expand more during recessions. However, if is only the left tail that increases during recession—an asymmetric increase in dispersion—the proportion of firms observing growth rate below the mean does not need to be equal to the proportion above the mean. The empirical evidence that we show here support the view that recessions are periods in which the left tail of the distribution of growth rates of sales expands without any significant change in the upper tail of the distribution.

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. Orlik and Veldkamp [2014] study how uncertainty arises proposing a model in which individuals do not know the true distribution of shocks. Uncertainty increases when unexpected negative realizations occur. 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 a different source of risk (downside 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 studying how asymmetric changes in risk could generate larger effects in economic activity than those found so far in the literature.

Finally, there is a growing literature that analyzes the 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 counter cyclical variation in dispersion but exhibit strong pro cyclical skewness. That is, during recessions the upper tail of the earnings growth rates distribution collapses, while the left tail becomes thicker, implying a greater probability of observing large negative shocks. Busch et al. [2015] find similar results for Sweden and Germany. Our approach and methodology are similar to theirs but our focus is on firm level variables. 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. Decker et al. [2015] document the declining trend in the skewness of the firm growth rate distribution in the U.S. They find that this decline is due to the drop in the number of young high-growth firms especially during the post-2000 period. Distante et al. [2013] characterize the distribution of firm level growth using a quantile regression approach. As in our paper, they find strong pro cyclical skewness while changes in the dispersion are in second order of importance.

2 Data

2.1 Sample Selection

The main data source is the CRSP/Compustat merged database, from which we obtain data on firm-level quarterly sales (SALEQ), cost of goods sold (COGSQ), total inventories (INVTQ), and 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. We also drop all firms under public administration or unclassified (two-digit SIC above 89). The main sample considers firms of CRSP 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. We complement this data with aggregate measure of prices and GDP per capita from FRED database.

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. In the following sections we contrast results with and without entry and exit of firms. Table I shows some basic statistics for each of the samples under study.

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 the Kelly's measure which is defined as

$$KSK_t = \frac{P90 - P50}{P90 - P10} - \frac{P50 - P10}{P90 - P10} \qquad \in [-1, 1].$$

Table I – Quarterly Sample Characteristics - Real Sales Growth

	All Firms	Exits >10 yrs	Exits >25 yrs
Number of Firms	20,553	8,473	1,999
Obs. (Firms/Quarter)	827,322	651,037	272,848
Firms per Quarter (Average)	4,060	3,180	1,332
Mean of $g_{i,t}$(Sales)	0.123	0.121	0.116
Std of g_{it}(Sales)	0.415	0.368	0.296
Coeff. Skew of $g_{i,t}$(Sales)	–0.224	–0.294	–0.418
Coeff. Kurt of $g_{i,t}$(Sales)	10.828	12.623	15.228

Note Nominal quarterly sales are deflated using the Urban CPI measure from FRED.

Relative to the third standardized moment (which is another measure of skewness), this measure has the advantage to be robust to potential outliers. Clearly this measure is equal to 0 if the distribution is symmetric, such as the Normal distribution. We also present results on the kurtosis of the distribution. As in the case of the skewness, we use a percentile-based measure of kurtosis instead of the fourth standardized moment. In particular, our preferred measure of kurtosis is Moors measure (Moors [1988]) which is defined as:

$$MKU_t = \frac{(E_7 - E_5) + (E_3 - E_1)}{E_6 - E_2},$$

where E_i is the i^{th} octile of the distribution. Similarly to Kelly's measure, Moor's measure of kurtosis weights the mass that is in the tails (the sum of the two components of the numerator) with the mass that is in the center of the distribution. In the case of a Normal distribution, Moors measure of kurtosis is equal to 1.23.

3 Time Varying Skewness

3.1 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), higher order 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 pro cyclical variation, staying mostly positive during expansions and declining sharply during recessions.

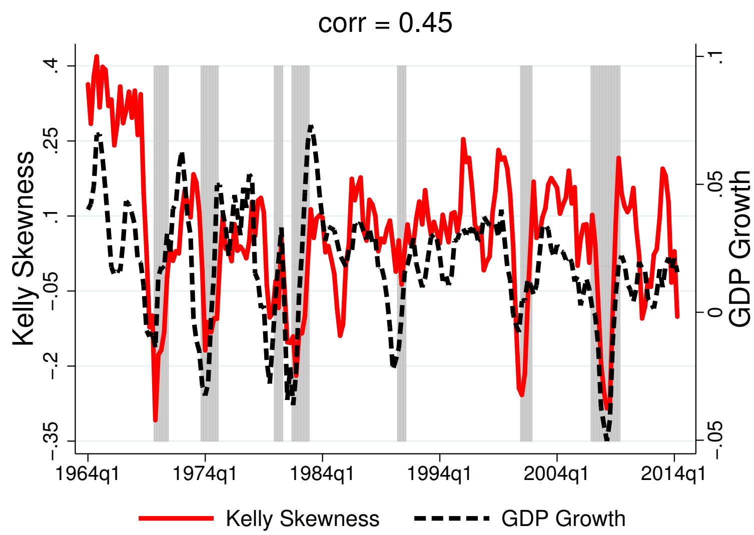
To get a sense of the magnitude of these changes, consider the Great Recession. Immediately before the recession, sales growth displayed a positive skewness. Kelly's measure was 0.10, implying that the upper tail, $P9050$, made up 55% of the overall $P9010$ dispersion, leaving 45% gap for $P5010$. With 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 0.22 down to –0.24) 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 pro cyclicality 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 counter cyclical, 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.

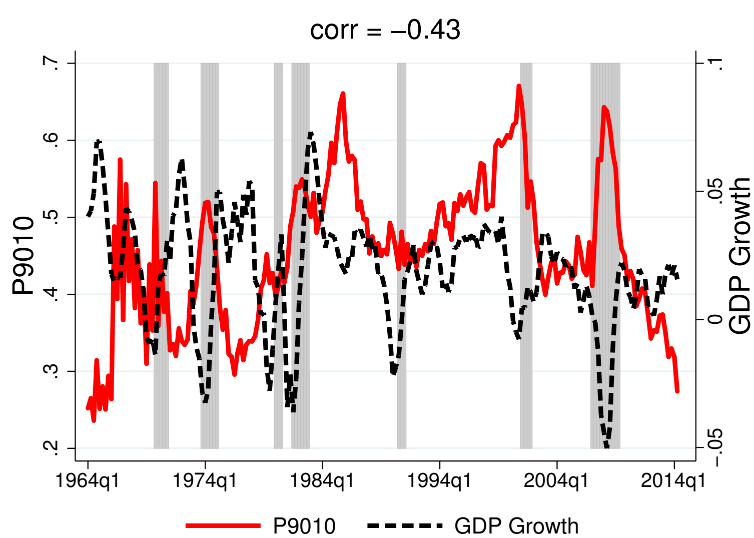
To take a closer look, figure 4 display the $P9050$ while figure 5 displays the $P5010$ differential. Notice that the dispersion above the median is a cyclical, and therefore, all the counter cyclicality observed in figure 3 must come from the lower section of the distribution, as is shown in figure 5. In other words, recessions are not characterized by an overall increase in dispersion but mostly by a large increase in the dispersion

Figure 2 – Cross Sectional Skewness of Sales Growth Distribution



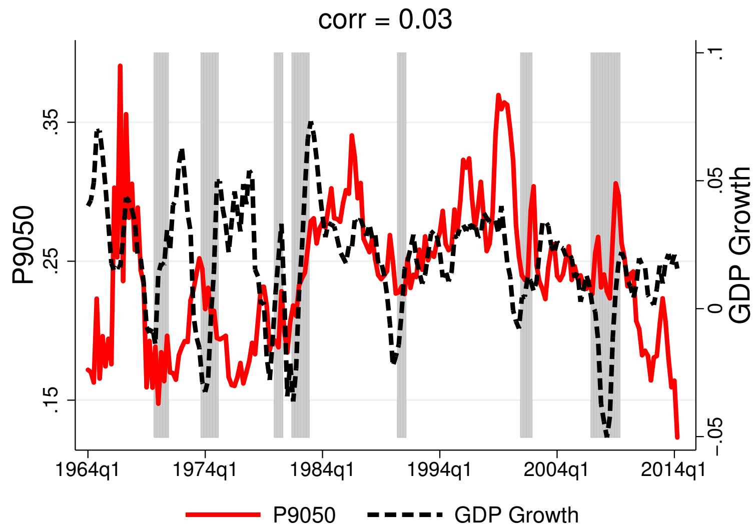
Note: The reported correlation is calculated considering the HP detrended series of the corresponding cross sectional moment and the growth rate of GDP per capita. For timing consistency, the growth of GDP per capita is measure as $g_{GDPt} = \log GDP_{t+1} - \log GDP_t$.

Figure 3 – Cross Sectional Dispersion of Sales Growth Distribution



Note: The reported correlation is calculated considering the HP detrended series of the corresponding cross sectional moment and the growth rate of GDP per capita. For timing consistency, the growth of GDP per capita is measure as $g_{GDPt} = \log GDP_{t+1} - \log GDP_t$.

Figure 4 – Dispersion Above the Median of Sales Growth Distribution



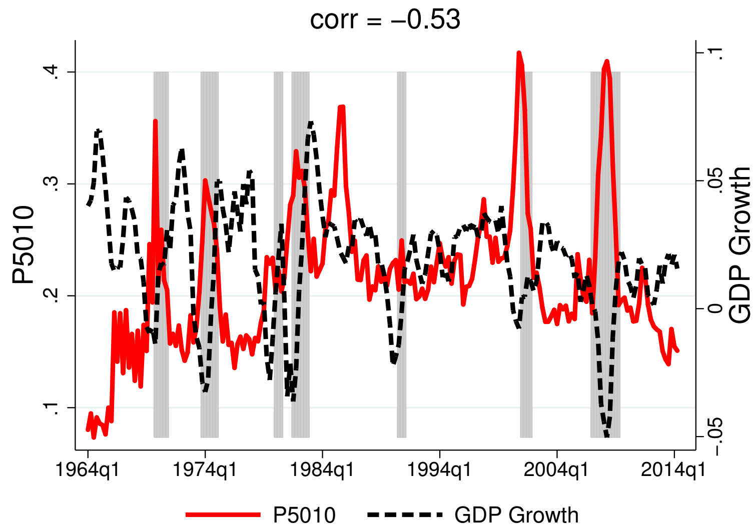
Note: The reported correlation is calculated considering the HP detrended series of the corresponding cross sectional moment and the growth rate of GDP per capita. For timing consistency, the growth of GDP per capita is measure as $g_{GDPt} = \log GDP_{t+1} - \log GDP_t$.

in the lower part of the distribution with little change in the dispersion of the upper half. That is, 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.

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 constant, a linear trend, and a recession dummy—equal to 1 if the corresponding calendar quarter is part of a recession (β_{Rec}). We find that dispersion is counter-cyclical. The third column shows that Kelly's skewness declines during a recession by 0.19 (a coefficient that is highly significant with a t-stat of –6.47). The next two columns (4 and 5) show that P9050 changes very little in recessions, whereas P5010 increases strongly, from an expansion value of 0.17 up to 0.25 in recessions.[1]

[1]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.

Figure 5 – Dispersion Below the Median of Sales Growth Distribution



Note: The reported correlation is calculated considering the HP detrended series of the corresponding cross sectional moment and the growth rate of GDP per capita. For timing consistency, the growth of GDP per capita is measure as $g_{GDPt} = \log GDP_{t+1} - \log GDP_t$.

Table II – Cross Sectional Moments During Recessions

	(1) IQR	(2) $P9010$	(3) KSK	(4) $P9050$	(5) $P5010$	(6) MKU
β_{Rec}	0.0352***	0.0640**	–0.190***	–0.0138	0.0778***	–0.0790*
	(3.78)	(3.29)	(–6.47)	(–1.45)	(5.47)	(–2.18)
$Cons$	0.155***	0.391***	0.146***	0.223***	0.168***	1.665***
	(17.54)	(15.79)	(3.49)	(15.28)	(11.41)	(30.25)
N	202	202	202	202	202	202

Note: β_{Rec} is the coefficient of a regression of the corresponding cross sectional moment on a recession dummy, constant, and linear trend (not shown). Newey-West t-statistics are included in parentheses (maximum lag length considered: 4). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 two alternative samples of firms. In the first sample (denoted the Y10-sample) we restrict the panel of

CRSP 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 CRSP firms that we observe for at least two years (Y1 sample).

The first two panels of table III present the same analysis using a less restrictive sample. In the first panel we consider firms that are observed for 10 years or more while in the second panel we consider all the firms observed for 2 years or more. 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.

In the previous results we have not considered the entry and exit of firms although the definition of the growth rate that we are using here is useful in the respect. In particular, upon entry, the growth rate of a particular variable (i.e. sales) is equal to 2, while in the period of exit it is equal to –2. Since entry and entry fluctuate with the economic cycle, it is possible that they have significant impact in our measures of cross sectional dispersion, skewness, and the rest of the cross sectional moments. Figure 6 shows the time series and corresponding correlation with the GDP growth of our measures of dispersion and our measure of skewness. The results are similar when compared to the same measures without considering entry and exit. The bottom of table III shows a regression of our measures of dispersion, skewness, and kurtosis on the recession indicator, a constant, and a linear trend. We find an even stronger decline of skewness during recession.

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? To answer this question the first panel of table IV shows the results from a regression of the 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 row denoted by $\beta_{gGDP} \times \sigma_{gGDP}$ 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 0.074.

For completeness, the bottom panel of table IV shows the relation between the same

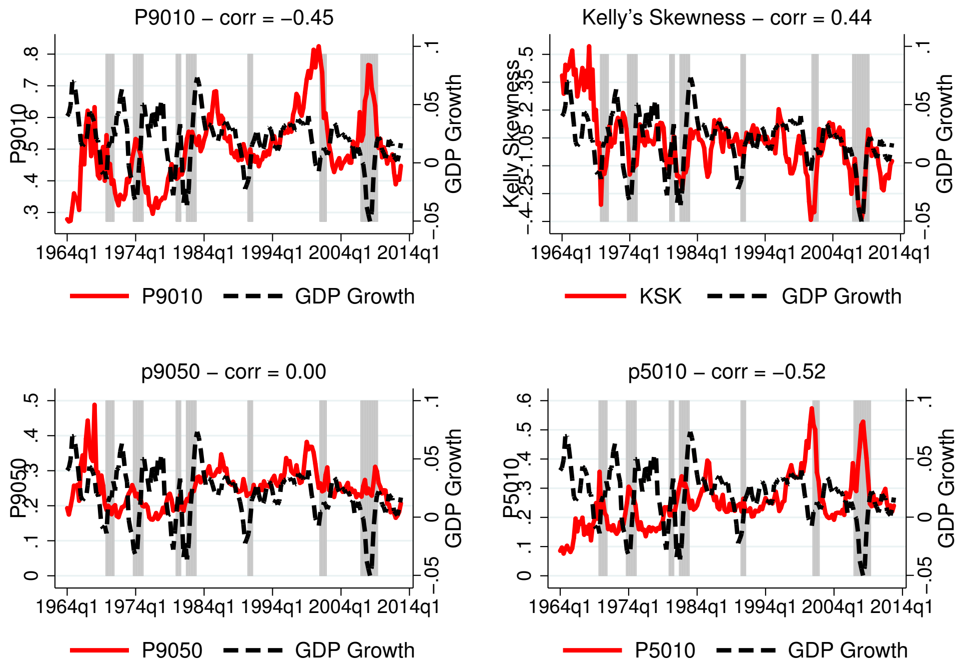
Table III – Moments Of The Distribution During Recessions

	(1) IQR	(2) $P9010$	(3) KSK	(4) $P9050$	(5) $P5010$	(6) MKU
			Firms with 10 or more years of data			
β_{Rec}	0.028**	0.042	–0.142***	–0.0185	0.061***	–0.072*
	(3.11)	(1.78)	(–5.22)	(–1.34)	(4.17)	(–2.08)
$Cons$	0.174***	0.440***	0.118**	0.244***	0.196***	1.655***
	(16.10)	(13.37)	(2.97)	(13.19)	(10.78)	(35.66)
N	202	202	202	202	202	202
			All Firms			
β_{Rec}	0.0270*	0.036	–0.132***	–0.021	0.057**	–0.079
	(2.45)	(1.05)	(–4.80)	(–1.17)	(2.88)	(–1.96)
$Cons$	0.183***	0.472***	0.0968*	0.254***	0.217***	1.678***
	(13.74)	(10.97)	(2.45)	(11.53)	(9.08)	(33.75)
N	202	202	202	202	202	202
			Entry and Exit			
β_{Rec}	0.037***	0.045	–0.188***	–0.029*	0.074***	–0.152*
	(3.54)	(1.82)	(–6.07)	(–2.32)	(4.12)	(–2.15)
$Cons$	0.160***	0.380***	0.213***	0.238***	0.142***	1.638***
	(18.35)	(11.56)	(5.00)	(10.31)	(8.97)	(14.31)
N	202	202	202	202	202	202

Note: β_{Rec} is coefficient of a regression of the corresponding cross sectional moment on a recession dummy, constant, and linear trend (not shown). Newey-West t-statistics are included in parentheses (maximum lag length considered: 4). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

moments and the civilian employment growth rate. In this case we also find a strong relation between this measure of aggregate activity and the skewness and the dispersion below the median. The last line shows how much each moments changes when the employment growth rate varies in one standard deviation.

Figure 6 – Cross Sectional Moments with Entry and Exit of Firms



Note: The reported correlation is calculated considering the HP detrended series of the corresponding cross sectional moment and the growth rate of GDP per capita. For timing consistency, the growth of GDP per capita is measure as $g_{GDPt} = \log GDP_{t+1} - \log GDP_t$.

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 linear 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, cohort, and industry dummies, firm size (employment), and aggregate economic conditions (growth rate of GDP per capita). As in previous sections, the base line sample consists on firms

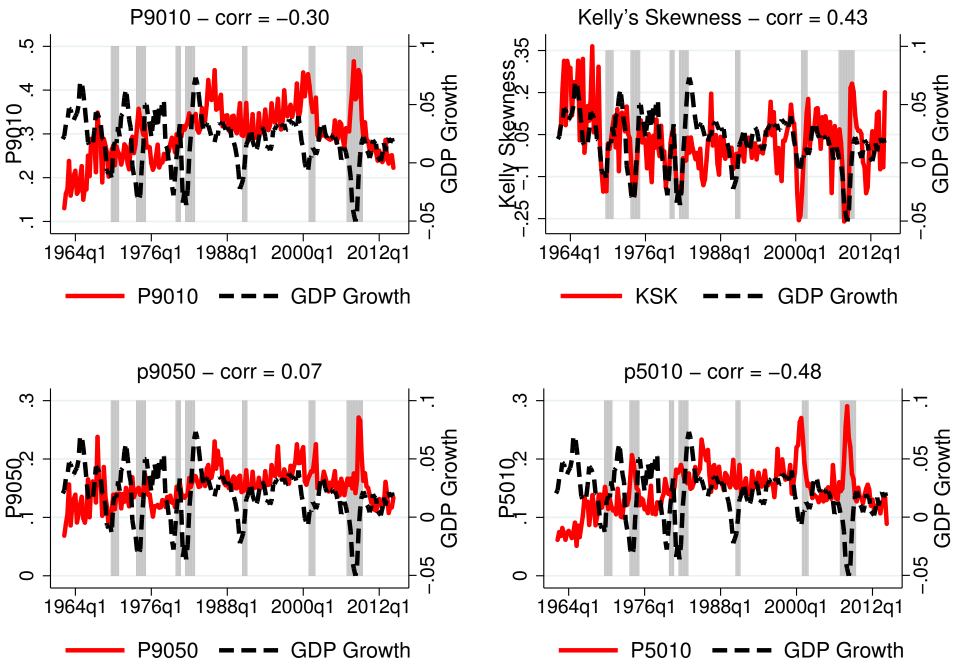
TABLE IV – BUSINESS CYCLE AND CROSS-SECTIONAL MOMENTS - GDP GROWTH

	(1) IQR	(2) $P9010$	(3) KSK	(4) $P9050$	(5) $P5010$	(6) MKU
			Growth rate of GDP Per capita			
$\beta_{g_{GDP}}$	–0.586**	–0.931*	3.231***	0.298	–1.230***	1.636*
	(–2.90)	(–2.17)	(5.08)	(1.48)	(–3.86)	(2.20)
$Cons$	0.179***	0.430***	0.0179	0.212***	0.218***	1.604***
	(17.58)	(19.62)	(0.40)	(14.92)	(14.44)	(27.85)
N	202	202	202	202	202	202
$\beta_{g_{GDP}} \times \sigma_{g_{GDP}}$	–0.013	–0.021	0.074	0.007	–0.029	0.038
			Growth Rate of Employment			
β_{Emp}	–1.134***	–2.091***	4.544***	0.140	–2.231***	2.145
	(–4.20)	(–3.41)	(4.63)	(0.37)	(–5.48)	(1.93)
$Cons$	0.190***	0.456***	–0.004	0.217***	0.239***	1.596***
	(16.20)	(17.12)	(–0.07)	(12.61)	(13.79)	(26.10)
N	202	202	202	202	202	202
$\beta_u \times \sigma_{g_{Emp}}$	–0.019	–0.034	0.075	0.002	–0.037	0.035

Note: $\beta_{g_{GDP}}$ (β_{Emp}) is the coefficient of a regression of the corresponding cross sectional moment on the growth rate of GDP per capita (growth rate of aggregate civilian employment), a linear trend (not shown), and a constant. Newey-West t-statistics are included in parentheses (maximum lag length considered: 4). For timing consistency, the growth of GDP per capita is measure as $g_{GDPt} = \log GDP_{t+1} - \log GDP_t$. In the sample period the standard deviation of the GDP growth was 2.3 percent. The growth of employment is measure as $g_{et} = \log Emp_{t+1} - \log Emp_t$. In the sample period the standard deviation of the employment growth was 1.6 percent.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. T-stats in parenthesis.

that we observe for 25 years or more but the results are robust to different sample selection. 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. Figure 7 shows the same cross sectional moments that we have calculated before for the case of sales

Figure 7 – Cross Sectional Moment of Residuals



growth but now using the residuals of the linear model. In each panel, the black 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. Second, here we also find that all the counter cyclicality of dispersion is coming from the left tail of the distribution.

3.2 Macroeconomic Skewness

In this section we study the cyclicality of skewness at macroeconomic level. For doing that, we use a panel of countries for which we collect quarterly GDP per capita and daily values of stock price indexes. Using the quarterly measures of GDP per capita we calculate the growth rate of GDP. Then, for each country we calculate time series of dispersion and skewness of the growth rate of GDP per capita using a trailing window of 13 quarter. That is, for each quarter t, the dispersion is measured as the standard deviation (or the difference between the 90th and the 10th percentiles) of the growth rate of GDP per capita between periods t and $t-12$ to have a total of 13 quarters. In the case of skewness we calculate the coefficient of skewness and Kelly's measure over the same window. Similarly, for the stock price indexes, first we calculate daily returns, and then we obtain measures of dispersion and skewness over the same 13 quarters. Then, we use these measures in a series of panel regressions. The results are shown in table V. In each column the dependent variable is the growth rate of GDP per capita of country i in the quarter t. For instance, in column (1) we regress the growth rate of GDP per capita over the time series of the standard deviation and a full set of country and quarter fixed effects. The corresponding coefficient is negative and statistically significant indicating, as expected, that dispersion at macroeconomic level is counter cyclical. In column (2) we regress the time series of the GDP growth on the time series of skewness. In this case the coefficient is positive and significant, indicating that the skewness is pro cyclical, as we argue in the previous section using firm level data. Columns (3) and (4) show similar results but now using the $P9010$ and the Kelly's measure of skewness. Columns (5) to (10) show that dispersion of daily returns are counter cyclical, the coefficient associated to the standard deviation and the $P9010$ are negative and statistically significant, while skewness is again pro cyclical.

To get a sense of the differences in the dispersion and skewness during different phases of the economic cycle we construct figure 8 which shows the value of different measures of dispersion and skenwess averaged within deciles of the country specific GDP growth distribution. To create this figure we first calculate the deciles of the GDP growth distribution within each country. Then, we pool all the country-quarter observations that belong to a given decile and we take the average of the dispersion and skewness measures across all those observation. Then, in the figure, a bar above zero indicates that the dispersion (skewness) is higher than average in the corresponding decile of the GDP growth distribution. The upper panel show the resulting figure for different measures of dispersion, which are clearly declining as we move from lower to higher deciles of the growth rate distribution with the exception of the GDP growth dispersion at the top of the distribution. However above the mean, the dispersion observed at higher deciles of the GDP growth distribution is much lower than at the bottom of the distribution. Overall, this indicates that dispersion is counter cyclical. Now, the lower panel shows the result for different measures of skewness. Here the skewness is below average at lower deciles of the growth rate distribution, stays around zero in the middle of the distribution, and becomes positive as we move towards the upper decile of the distribution. This indicate that skenwess is pro cyclical: when the economy is not doing well, the distribution of GDP growth and daily stock returns is very left skewed, during normal times, both distribution are fairly symmetrical, while the economy is in the upper end of the GDP growth distribution, both distribution are positive skewed.

Figure 8 – Macroeconomic Dispersion and Skewness

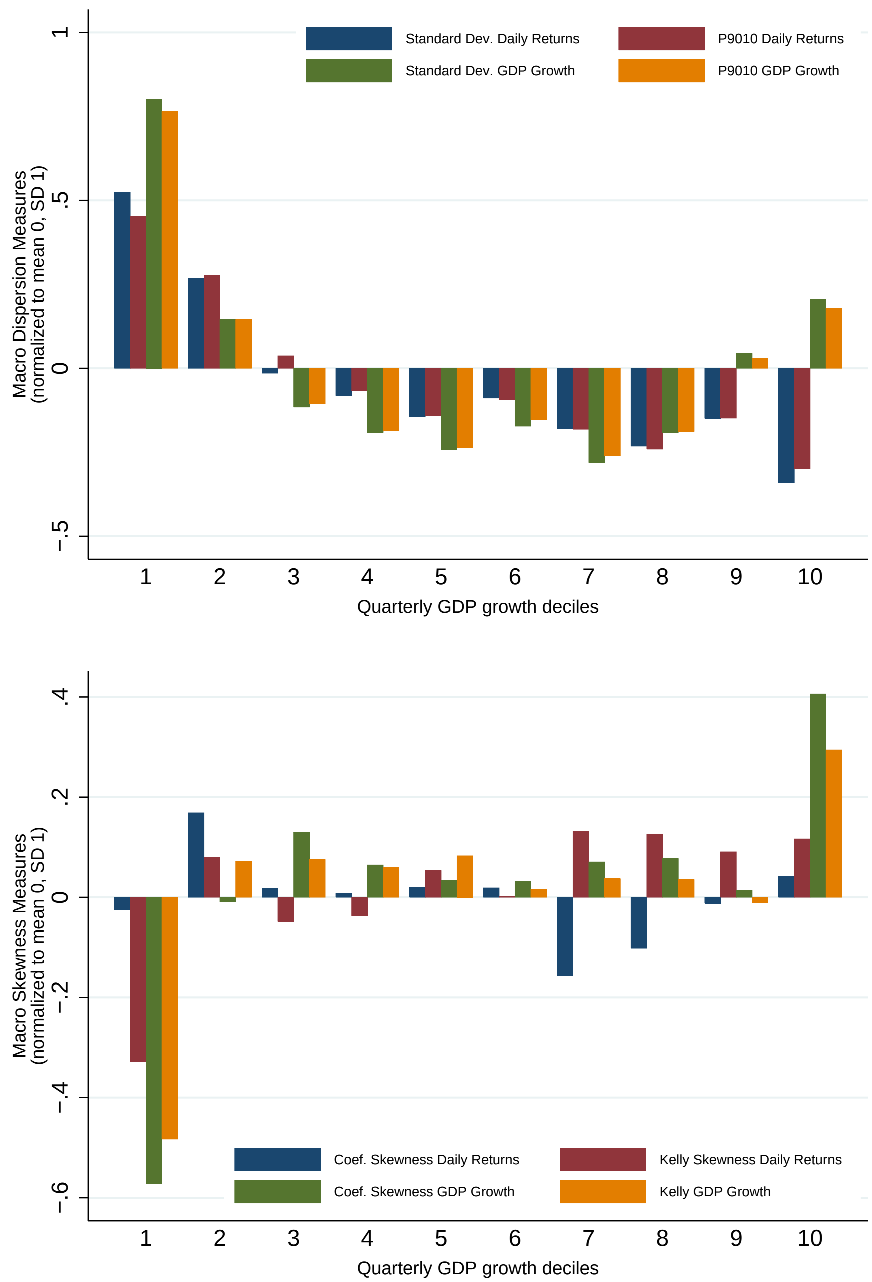


Table V – Macroeconomic Dispersion and Skewness

	GDP Growth				Daily Stock Returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SD_{i,t}$	-0.394***				-1.335***			
	(-3.29)				(-2.87)			
$SK_{i,t}$		0.00442***				0.00138		
		(3.50)				(1.38)		
$P9010_{i,t}$			-0.152***				-0.538**	
			(-3.18)				(-2.46)	
$KSK_{i,t}$				0.00416**				0.0905***
				(2.05)				(4.19)
R^2	0.658	0.650	0.657	0.648	0.714	0.705	0.712	0.723
N	5795	5795	5795	5795	2817	2817	2817	2817
Freq.	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly
Years	1970-2014	1970-2014	1970-2014	1970-2014	1985-2014	1985-2014	1985-2014	1985-2014
Ctry-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Country	Country	Country	Country	Country	Country	Country	Country

Note: Each column reports the results from a country - quarter OLS panel regression including a full set of country and quarter fixed effects. In each column, the dependent variable is growth rate of the real GDP in US dollars of 2010 of country i between quarter t and the same quarter of the previous year. The independent variables in column 1 and 4 are moments of the growth rate of GDP. The independent variables in columns 5 and 8 are moments of the distribution of daily returns of a stock price index of country i. Then, to calculate the moments of GDP growth distribution (daily returns) in quarter t we pool all the observations between quarters $t-12$ and t to make a total of 13 quarters.. Standard errors are clustered at country level and reported in parentheses below the point estimates. $***$ denotes 1%, $**$ denotes 5%, and $*$ denotes 10% significance respectively.

Table VI – Distribution of Observations by Sector

Sector	Observations	%
Agriculture and Extraction	13,863	5.08
Construction	3,952	1.45
Manufacturing	137,453	50.38
Transportation and Utilities	38,428	14.08
Trade	25,445	9.33
FIRE	31,320	11.48
Services	22,387	8.20
Total	272,848	100.0

4 Robustness

Skewness in different sectors

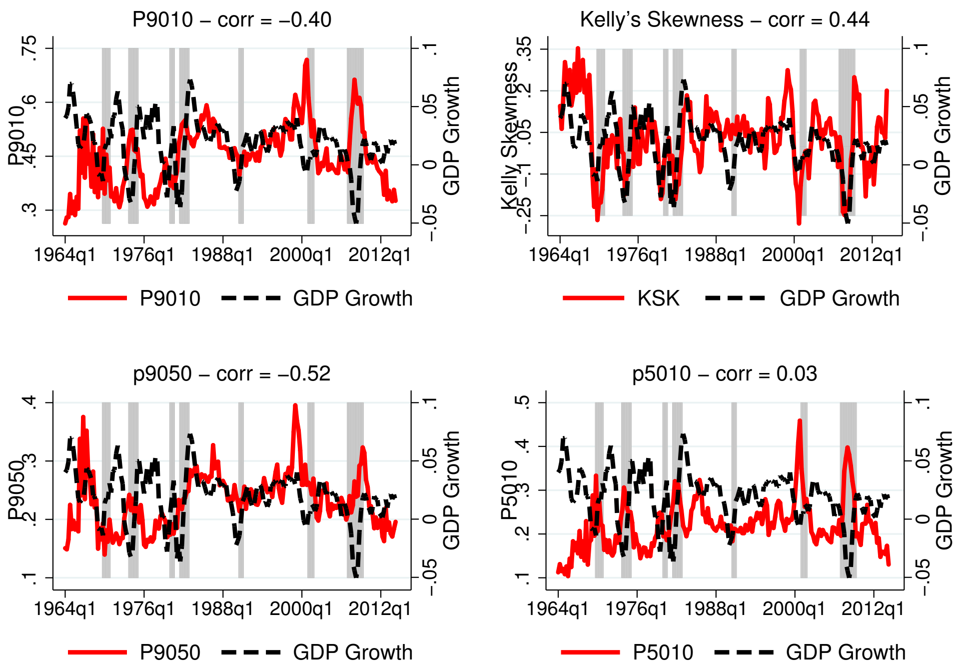
Here we show that the results presented in previous section are not driven by any sector in particular. To see this, here we split the sample of firms with more than 25 years of data in 7 broad categories based on the SIC identification reported in CRSP. The Table VI shows the number of firms-quarter observations in each of the sectors.

Figure 9 shows our measure of dispersion, skewness, and kurtosis for the sample of manufacturing firms that we observe for 25 years or more. As in the complete sample, here we also find that skewness is pro cyclical and that most of the increase in the dispersion observed during recession comes from the left tail of the distribution.

Figure 10 shows the time series of our measure of skewness for the rest of the sectors (solid line) along with the growth rate of GDP per capita (dashed line). 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 for 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 11 in which the solid line is the difference between the 90th and the 10th percentiles in each sector.

To complete the analysis, Table VII 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. The last column shows the same regression using the entire sample. We find that in every sector the partial correlation between the skewness of the distribution of sales growth and the dummy of recessions is negative although is not statistically significant for agriculture and mining (Extraction) and for Construction.

Figure 9 – Cross Sectional Moments in Manufacturing



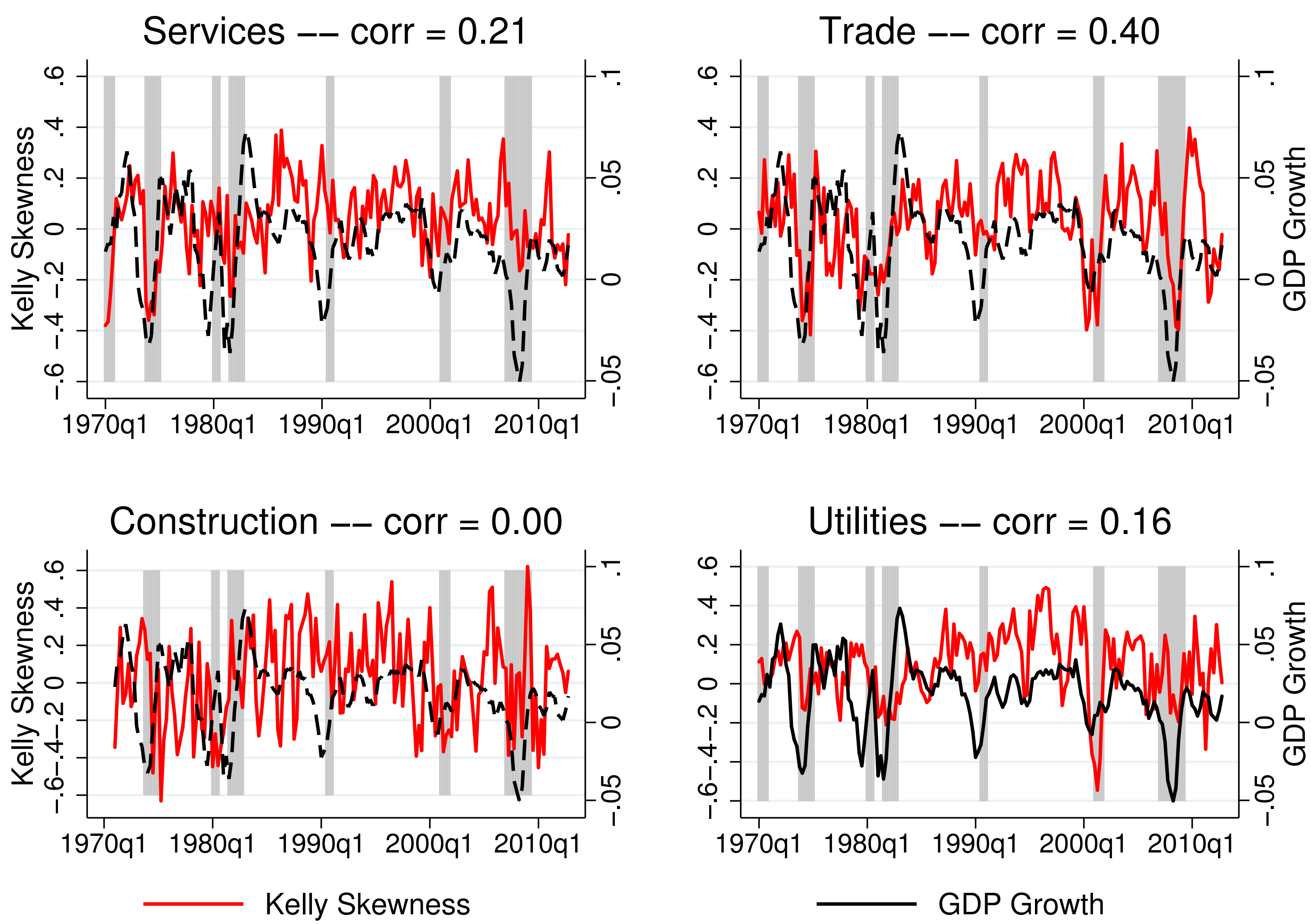
Note: The reported correlation is calculated considering the HP detrended series of the corresponding cross sectional moment and the growth rate of GDP per capita. For timing consistency, the growth of GDP per capita is measure as $g_{GDPt} = \log GDP_{t+1} - \log GDP_t$.

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 weighted measures of dispersion and skewness using, as weights, the employment and sales level. Figure 12 display three measures of skewness and the growth rate of GDP per capita. The top of the figure shows the sample correlation. Both weighted measures show the same patters displayed by the unweighted measure, however, the sales weighed measure (green circled line) show a lower correlation than the other two measures although is still positive.

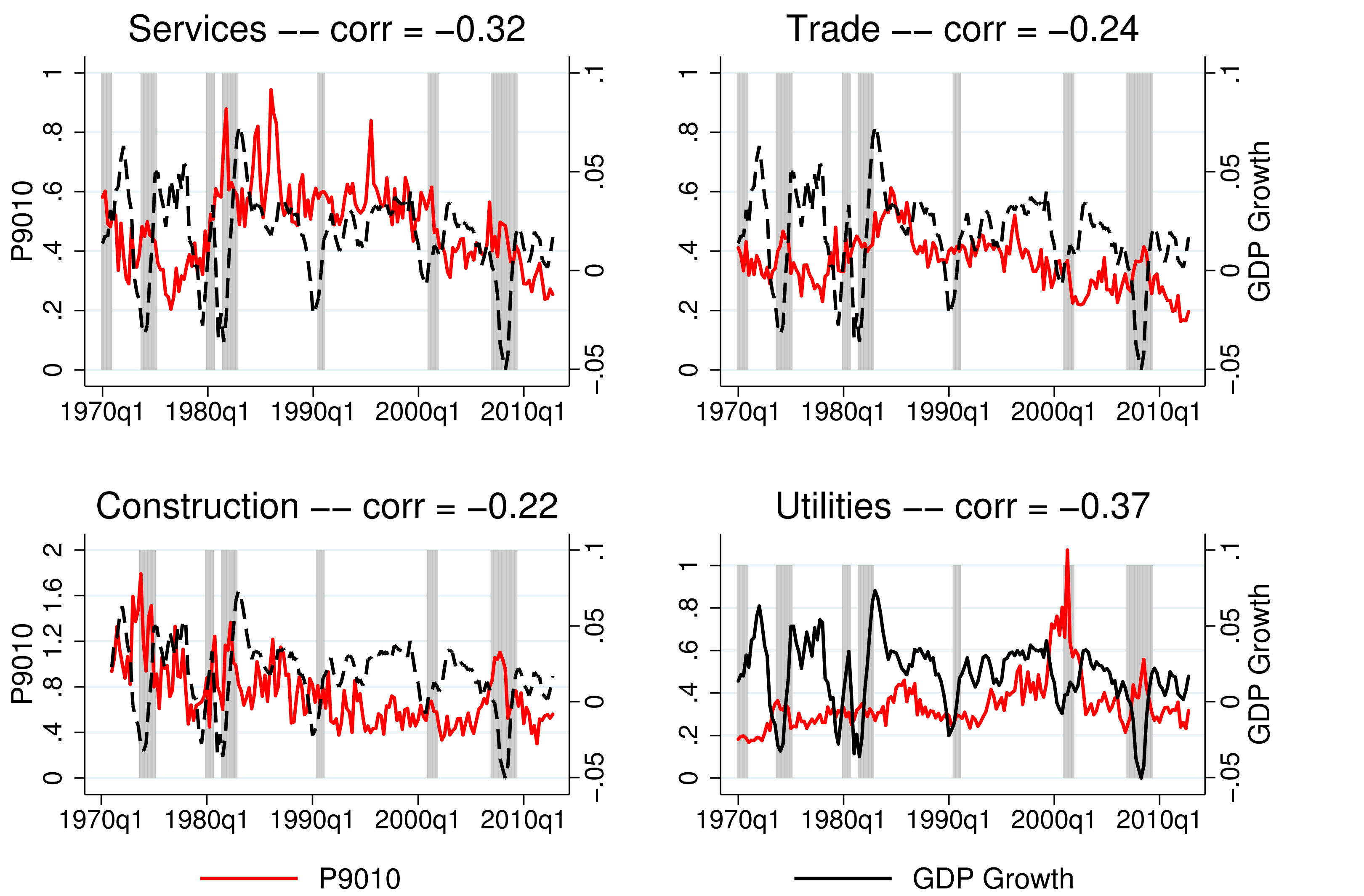
A second way to control for the wide differences in the size of the firms present in CRSP is to separate them in different size-bins and then calculate the different cross sectional moment within the groups. To this end we need a measure of the size of each

Figure 10 – Skewness in Different Sectors



Note: The reported correlation is calculated considering the HP detrended series of the corresponding cross sectional moment and the growth rate of GDP per capita. For timing consistency, the growth of GDP per capita is measure as $g_{GDPt} = \log GDP_{t+1} - \log GDP_t$.

Figure 11 – Dispersion in Different Sectors.



Note: The reported correlation is calculated considering the HP detrended series of the corresponding cross sectional moment and the growth rate of GDP per capita. For timing consistency, the growth of GDP per capita is measure as $g_{GDPt} = \log GDP_{t+1} - \log GDP_t$.

Table VII – Sector Regressions of Skewness on Recession Dummy

	(1)	(2)	(3)	(4)
	Manufacture	Extraction	Construction	Trans. & Util.
β_{Rec}	–0.140***	–0.031	–0.046	–0.174***
	(–5.27)	(–0.86)	(–0.77)	(–4.25)
$cons$	0.0843*	0.150**	–0.001	0.118***
	(2.46)	(2.92)	(–0.20)	(4.33)
N	202	201	192	202
	Trade	Fin. and Real State	Services	Sample
β_{Rec}	–0.174***	–0.141***	–0.181***	–0.188***
	(–4.21)	(–3.46)	(–3.80)	(–6.07)
$Cons$	0.132**	0.063	0.120**	0.213***
	(2.88)	(1.32)	(3.00)	(5.00)
N	202	202	202	202

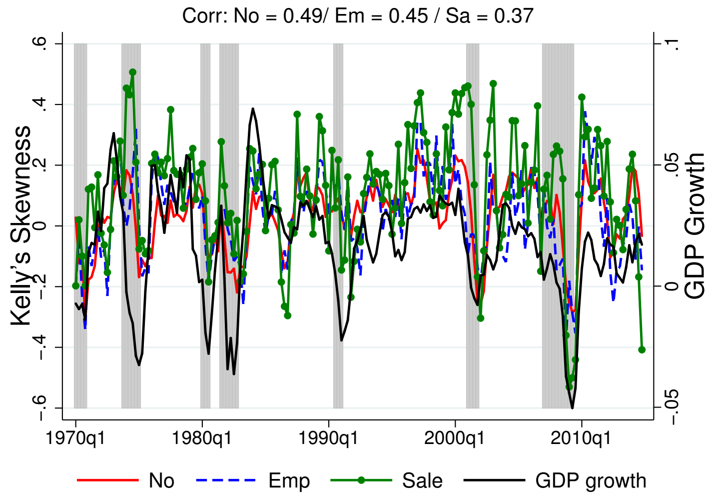
Note: β_{Rec} is coefficient of a regression of the corresponding cross sectional moment on a recession dummy, a linear trend (not shown), and a constant. Newey-West t-statistics are included in parentheses (maximum lag length considered: 4). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

firms which we construct as follows. For period i in quarter q, in year y, we obtain an average measure of employment, $\bar{e}_{iq}$ as the average of the employment of the firm i between years $y-3$ and $y-1$. Then we form four size groups based on the quartiles of the employment distribution of $\bar{e}_{iq}$ within each industry (2 digit SIC classification) and we calculate the time series of our cross sectional moments from 1970 to 2014. The figures 13 and 14 show the results. Most notably, within each group the evolution of skewness and dispersion follows the same pattern that we have shown in previous sections.

Profits, Inventories, 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, inventories, and annual employment. Figure 15 shows the evolution of the skewness for these variables. For comparison, we shows the time series of sales growth for the same

Figure 12 – Weighted and Unweighted Measures of Cross Sectional Skewness



Note: The reported correlation is calculated considering the HP detrended series of the corresponding cross sectional moment and the growth rate of GDP per capita. For timing consistency, the growth of GDP per capita is measure as $g_{GDPt} = \log GDP_{t+1} - \log GDP_t$.

period of time.

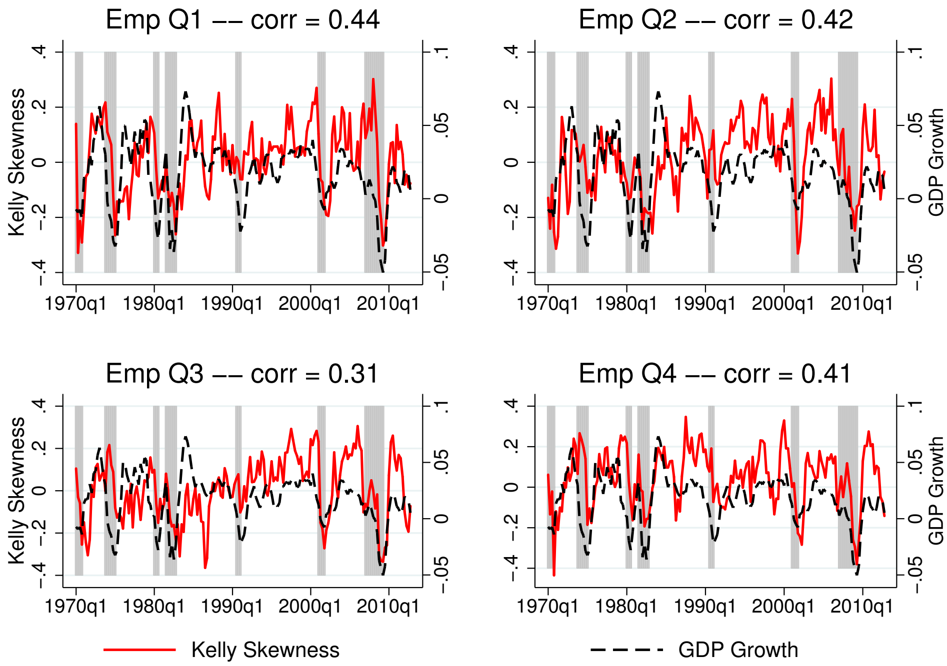
5 Panel analysis

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

Figure 13 – Skewness for different size-firms groups



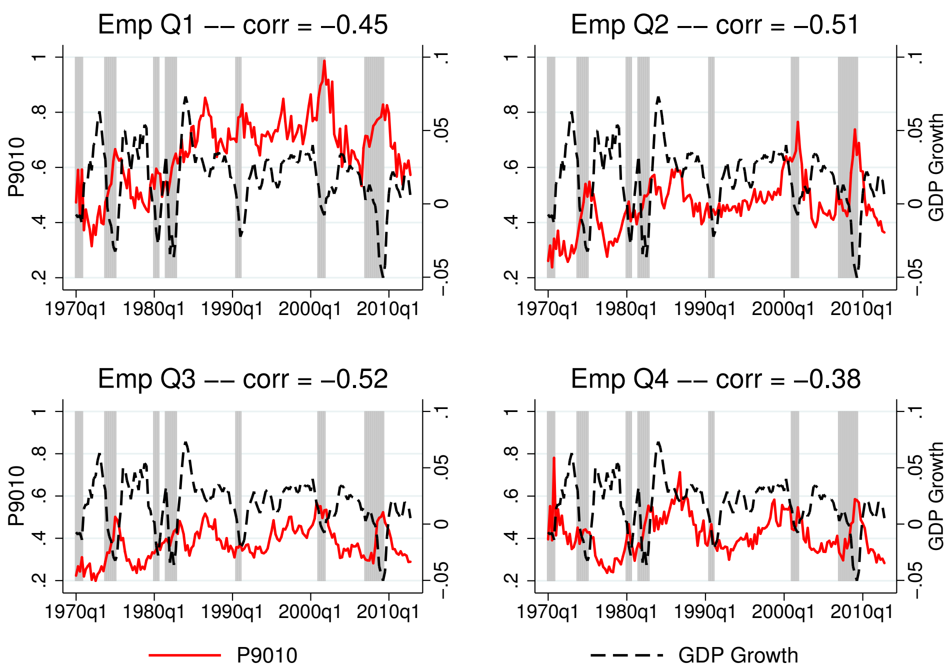
Note: The reported correlation is calculated considering the HP detrended series of the corresponding cross sectional moment and the growth rate of GDP per capita. For timing consistency, the growth of GDP per capita is measure as $g_{GDPt} = \log GDP_{t+1} - \log GDP_t$.

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, 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).[2]

The first set of results refers to conditional dispersion of the growth rate of sales distribution. The figure 16 shows, from top to bottom, the 90th, 50th and 10th percentile

[2]In each of the of the graphs the smoothing is done using local regression. We set the bandwidth to 0.7 although the results do not change substantially if we use other values for the bandwidth.

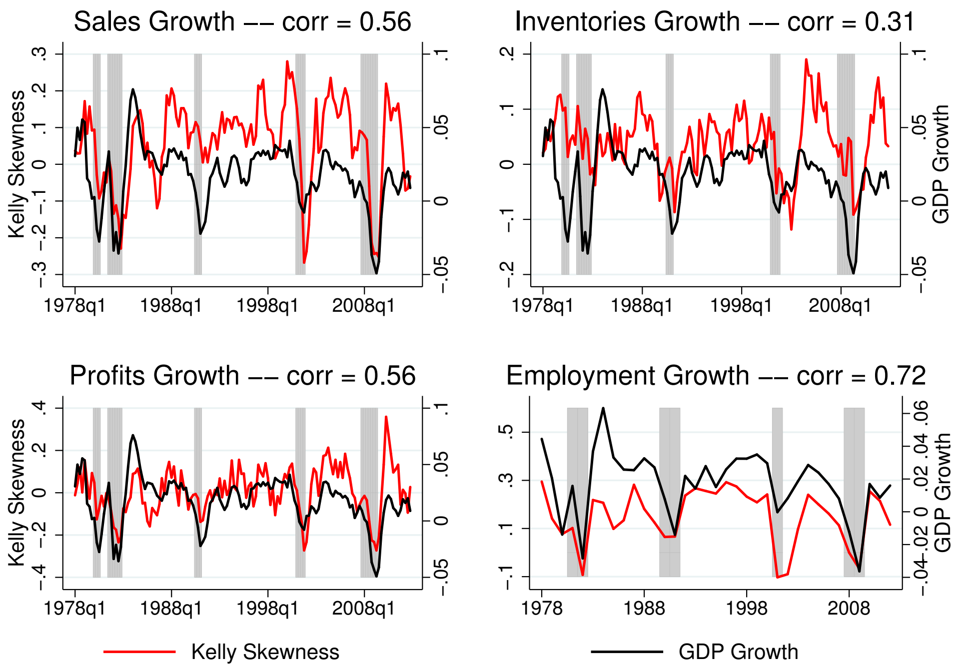
Figure 14 – Dispersion for different size-firms groups



Note: The reported correlation is calculated considering the HP detrended series of the corresponding cross sectional moment and the growth rate of GDP per capita. For timing consistency, the growth of GDP per capita is measure as $g_{GDPt} = \log GDP_{t+1} - \log GDP_t$.

of the distribution of the transitory shocks, $g_{t,t+4}$ against each percentile of the five-year 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 17 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 – Kelly Skewness for Different Variables



Note: The reported correlation is calculated considering the HP detrended series of the corresponding cross sectional moment and the growth rate of GDP per capita. For timing consistency, the growth of GDP per capita is measure as $g_{GDPt} = \log GDP_{t+1} - \log GDP_t$.

Figure 16 – Percentiles of the sales growth distribution (Transitory Shock, $g_{t,t+4}$)

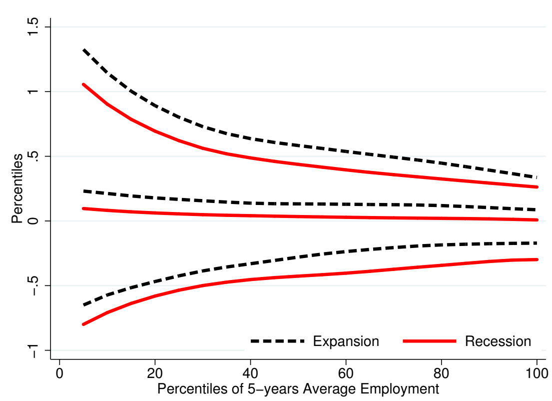
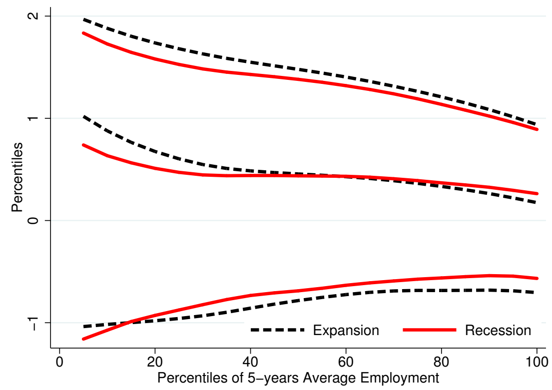
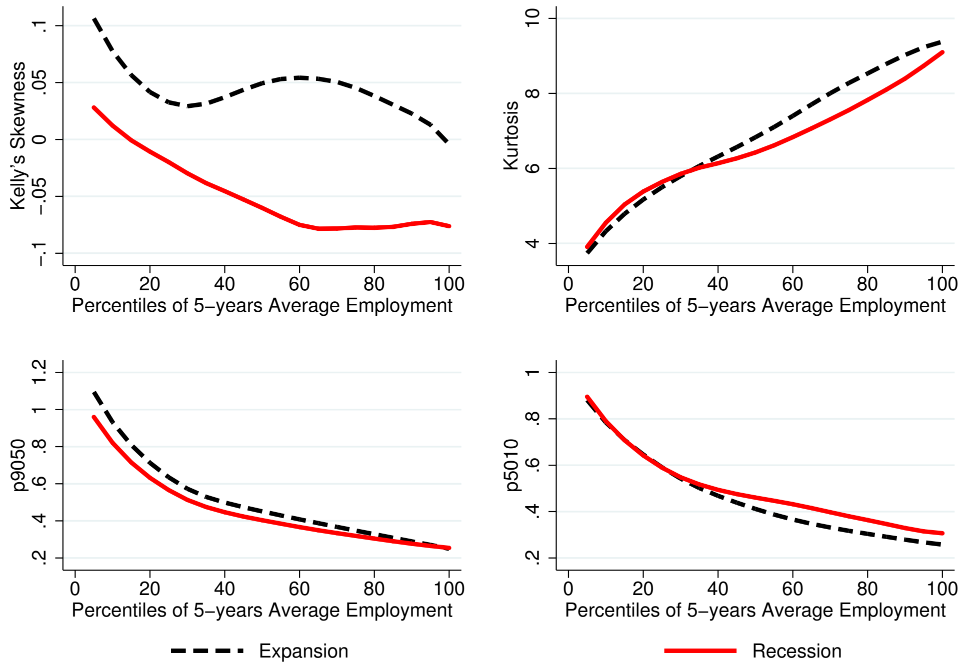


Figure 17 – Percentiles of the sales growth distribution (Permanent Shock, $g_{t,t+20}$)



Now we turn to higher order moments of the distribution of sales growth conditional on the size of the firm. The upper left panel of figure 18 displays the skewness of the cross sectional distribution (Kelly's skewness). Two things are worth to notice here. 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 comparison, the upper left panel figure 19 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. The bottom panels of figures 18 and 19 shows the $P9050$ and $P5010$ differential for the transitory and permanent shock.

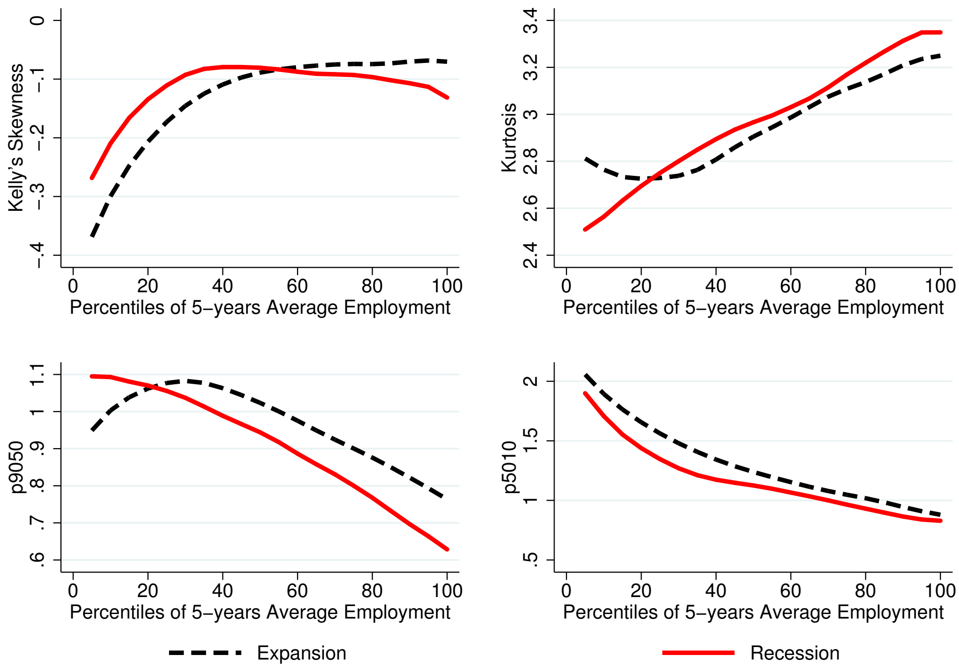
Figure 18 – Cross Sectional Moments - Transitory Shock, $g_{t,t+4}$



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, the upper right panel of figure 18 shows how the coefficient of kurtosis varies with the firm's size for a transitory shock in recessions and expansion. 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. The same pattern can be found in the case of the permanent shock as is shown in figure 19. 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 19 – Cross Sectional Moments - Permanent Shock, $g_{t,t+20}$



6 Cross Country Evidence

In this section we study the time series of the cross sectional moment discussed above using firm level data for a wide sample of countries. Despite the large heterogeneity in terms of data sources and economic conditions we find that our two main results regarding the procyclicality of skewness and the pro cyclicality of the dispersion below the median are robust.

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 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 Employees, and Cost of Goods Sold.

Table VIII – Data Availability O9-Sample

Country	Freq.	Percent	Cumulative	Start	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	100.00	1982	2013
Total	301,543	100			

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 VIII shows the distribution of observations for this sample across countries.[3]This data is complemented using real GDP growth per capita and Unemployment Rate from World Development Indicators, WDI.

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 co movement between the skewness, measured by the Kelly's skewness, and the economic activity, measured

[3]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.

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 20 and 21 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 VIII. Table IX displays the correlation between the growth of GDP per capita and the measure of skewness. The correlation has the expected positive sign for most of the countries with the exception of China and India.[4]

Dispersion

Now we turn to our measure of dispersion. Figure 22 and 23 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 X with the exception of Korea.

Upper and lower dispersion

Finally, we study the evolution of the dispersion above and below the median. Figures 24, 25, and 26 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 sample the dispersion above the median seems to decline during recessions and increases during economic booms (see U.S. for instance in figure 24). This evidence partially

[4]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, using bootstrapped standard errors and robust estimation of the variance covariance matrix to control for potential heteroskedasticity and autocorrelation. We do not find any significant change in the point estimates, however, the statistical significance changes for some countries, like Japan.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	USA	*CAN*	*GBR*	*AUS*	*DEU*	*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	0.082*	0.119*	0.032	0.062	0.022	0.041*
	(2.72)	(2.38)	(1.52)	(1.22)	(0.96)	(2.26)
R^2	0.436	0.088	0.413	0.031	0.153	0.314
N	30	30	30	29	29	29
	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	0.060*	–0.015	0.367	0.0834	–0.091*	–0.371
	(2.25)	(–0.40)	(1.74)	(1.82)	(–2.63)	(–0.051)
R^2	0.114	0.573	0.114	0.051	0.357	0.145
N	24	23	21	24	24	24

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 on wards. The results for the dispersion above the median are shown in table XI. 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 table XII.

Euro Zone and Latin America

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

TABLE X – 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	0.012	0.007	0.047	0.045
N	31	30	30	29	30	30
	JPN	KOR	CHN	IND	MYS	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	0.089	0.051	0.061
N. Obs	29	30	22	27	29	24

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

head quarters are in a country of European Union.[5] 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 27 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 $p9010$) and above the median ($p9050$) but counter cyclical dispersion below the median ($p5010$). This can be observed in the panel of table XIII that shows a set of regressions of the cross sectional moments on the growth rate of GDP per capita.

[5]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 XI – GDP Growth and Upper Dispersion ($p9050$) - Diff Countries

	(1)	(2)	(3)	(4)	(5)	(6)
	USA	*CAN*	*GBR*	*AUS*	*DEU*	*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	0.055	0.028	0.130	0.000	0.000	0.151
N	31	30	30	29	30	30
	JPN	*KOR*	*CHN*	*IND*	*MYS*	*TWN*
β_{gGDP}	0.0852	–0.006	–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	0.006	0.000	0.271	0.126	0.095	0.023
N	24	24	22	24	24	24

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 the bottom panel of table XIII.

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, 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. The top panel of table XIV shows a set

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

	(1)	(2)	(3)	(4)	(5)	(6)
	USA	CAN	GBR	AUS	DEU	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	0.034	0.045	0.015	0.226	0.004
N	31	30	30	29	30	30
	JPN	KOR	CHN	IND	MYS	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	0.039	0.490	0.100	0.180	0.423	0.226
N	24	24	22	24	24	24

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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, the bottom panel of table XIV 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.

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

TABLE XIII – CROSS SECTIONAL MOMENT AND GDP GROWTH

	(1) $p9010$	(2) $p7525$	(3) KSK	(4) $p9050$	(5) $p5010$	(6) Kur
			European Union			
β_{gGDP}	0.602	0.009	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	0.012	0.000	0.460	0.185	0.166	0.022
N	31	31	31	31	31	31
			Latin American			
β_{gGDP}	0.153	0.063	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***	0.037	0.263***	0.246***	13.96***
	(27.62)	(24.51)	(1.50)	(30.04)	(18.47)	(21.13)
R^2	0.006	0.005	0.169	0.128	0.019	0.003
N	16	16	16	16	16	16

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 XV shows the distribution of observations in the sample and time span covered in the sample for each country.

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

	(1) $p9010$	(2) $p7525$	(3) KSK	(4) $p9050$	(5) $p5010$	(6) Kur
	Annual Data (1962)					
β_{gGDP}	–1.436**	–0.757**	4.294***	–0.003	–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	0.000	0.274	0.188
N	50	50	50	50	50	50
	Annual Data (1984)					
β_{gGDP}	–0.017	–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***	–0.015	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	31	31	31	31	31	31

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 XVI shows the data availability for 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

Table XV – 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			

Table XVI – Data Availability R-Sample

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

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 28 and 29 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.[6] 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 by table XVII in which we show a series of regressions of our measure of skewness on the growth rate of GDP per capita for different countries. [7] For all countries, the coefficient of the growth rate of GDP per capita is positive and significant. We find similar results when one uses the growth rate of investment, shown in the middle panel of table XVII, or the growth rate of consumption, shown in the bottom panel of the same table.

Dispersion

As in previous sections, we measure dispersion as the 90th to 10th percentile differential. Figures 30 and 31 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 30 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 the top panel of table XVIII confirm a counter cyclical dispersion for the U.S. but for the rest of the countries for which 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 30), and therefore, is still possible to argue that, as in U.S., the dispersion increases during recessions. However with only one recession in the sample for most of the countries, its difficult to establish any statistical relation.

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

[7] 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 XVII – Skewness and Business Cycle - Global Compustat Sample

	(1) *USA*	(2) *UK*	(3) *DEU*	(4) *FRA*	(5) *POL*	(6) *SWE*	(7) *AUS*	(8) *BRA*
				Growth Rate of GDP Per capita				
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	–0.083***	0.086***	–0.002	–0.002	–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	60	56	36	36	39	36	61	60
				Growth Rate of Aggregate Investment				
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	–0.004	0.120***	0.011	0.041**	–0.102***	0.165***	0.0241	–0.073**
	(–0.30)	(6.69)	(0.35)	(3.11)	(–4.21)	(8.85)	(0.61)	(–2.96)
R^2	0.459	0.041	0.107	0.701	0.524	0.207	0.053	0.336
N	60	56	36	36	39	36	61	60
				Growth rate of Aggregate Consumption				
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	–0.083***	0.086***	–0.002	–0.002	–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	60	56	36	36	39	36	61	60

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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. The middle and bottom panels of table XVIII 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 in each of the countries. The first column of both tables shows the results for U.S., in which, as reported before, we find strong counter cyclical dispersion

TABLE XVIII – DISPERSION AND GDP GROWTH - GLOBAL COMPUSTAT SAMPLE

	(1) USA	(2) UK	(3) DEU	(4) FRA	(5) POL	(6) SWE	(7) AUS	(8) BRA
				Total Dispersion ($P9010$)				
β_{gGDP}	–2.305***	3.540**	–0.457	–0.742	1.124	0.0234	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	0.015	0.017	0.019	0.000	0.047	0.010
N	60	56	36	36	40	36	61	60
				Dispersion above the Median ($P9050$)				
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	0.014	0.184	0.042	0.130	0.262	0.038	0.128	0.064
N	60	56	36	36	40	36	61	60
				Dispersion below the Median ($P5010$)				
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	0.012	0.293	0.388	0.107	0.099	0.014	0.130
N	60	56	36	36	40	36	61	60

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$

below the median. What is interesting here is that in most of the countries we find pro cyclical dispersion above the median. The bottom panel of table XVIII 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.[8] 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.

The figures 33 and 34 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 32 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 XIX shows the results.[9] 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 complement this analysis using data of investment and consumption growth and we show the corresponding results in the middle and bottom panels of table XIX. 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.[10]

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

[9]These regressions are calculated using a robust estimator of the standard errors. As before, I run

Table XIX – Cross Sectional Moment and Business Cycle - European Firms

	(1) $p9010$	(2) $p7525$	(3) KSK	(4) $p9050$	(5) $p5010$	(6) KUR
			Growth Rate GDP Per Capita			
$\beta_{g_{GDP}}$	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	0.051	0.029	0.446	0.195	0.000	0.062
N	56	56	56	56	56	56
			Growth Rate of Aggregate Investment			
$\beta_{g_{Inv}}$	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	0.017	0.007	0.509	0.132	0.017	0.036
N	56	56	56	56	56	56
			Growth Rate of Aggregate Consumption			
$\beta_{g_{Con}}$	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	0.049	0.358
N	56	56	56	56	56	56

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$

a full set of robustness checks. There is not significant changes in the point estimates.

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

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 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 XX 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.

Table XX – Distribution of Observations - O10 Sample

Country	Freq.	Percent	Cum.	Start	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			

6.3.2 Results

Skewness and dispersion

Figures 35 and 36 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 37 and 38 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 39 and 40 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.

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.[11]

Figure 41 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 42 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

[11]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

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 43. If any, the differences between private and public firms are just in terms of levels.

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Figure 20 – Osiris: Skewness and GDP Growth

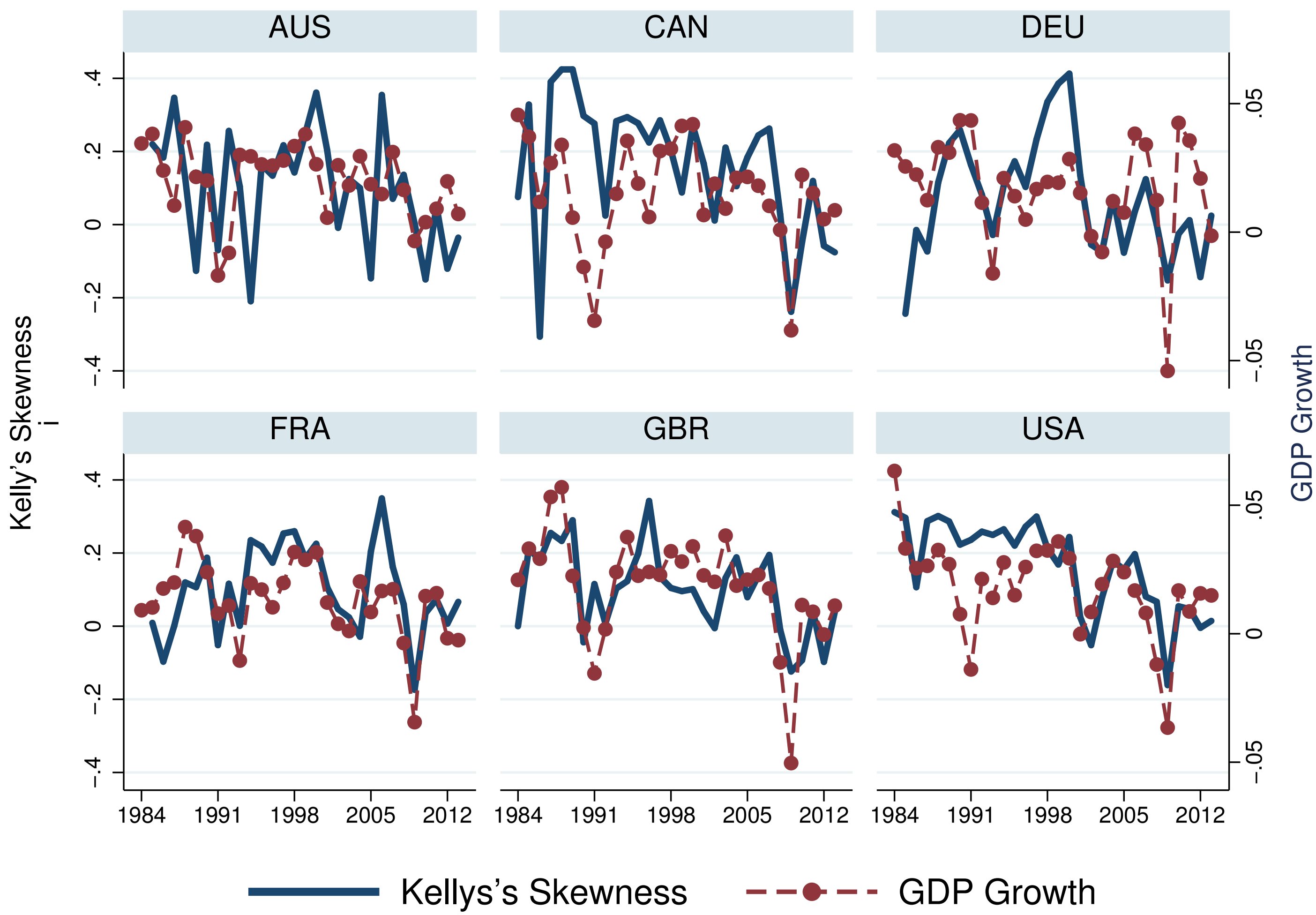

Figure 21 – Osiris: Skewness and GDP Growth

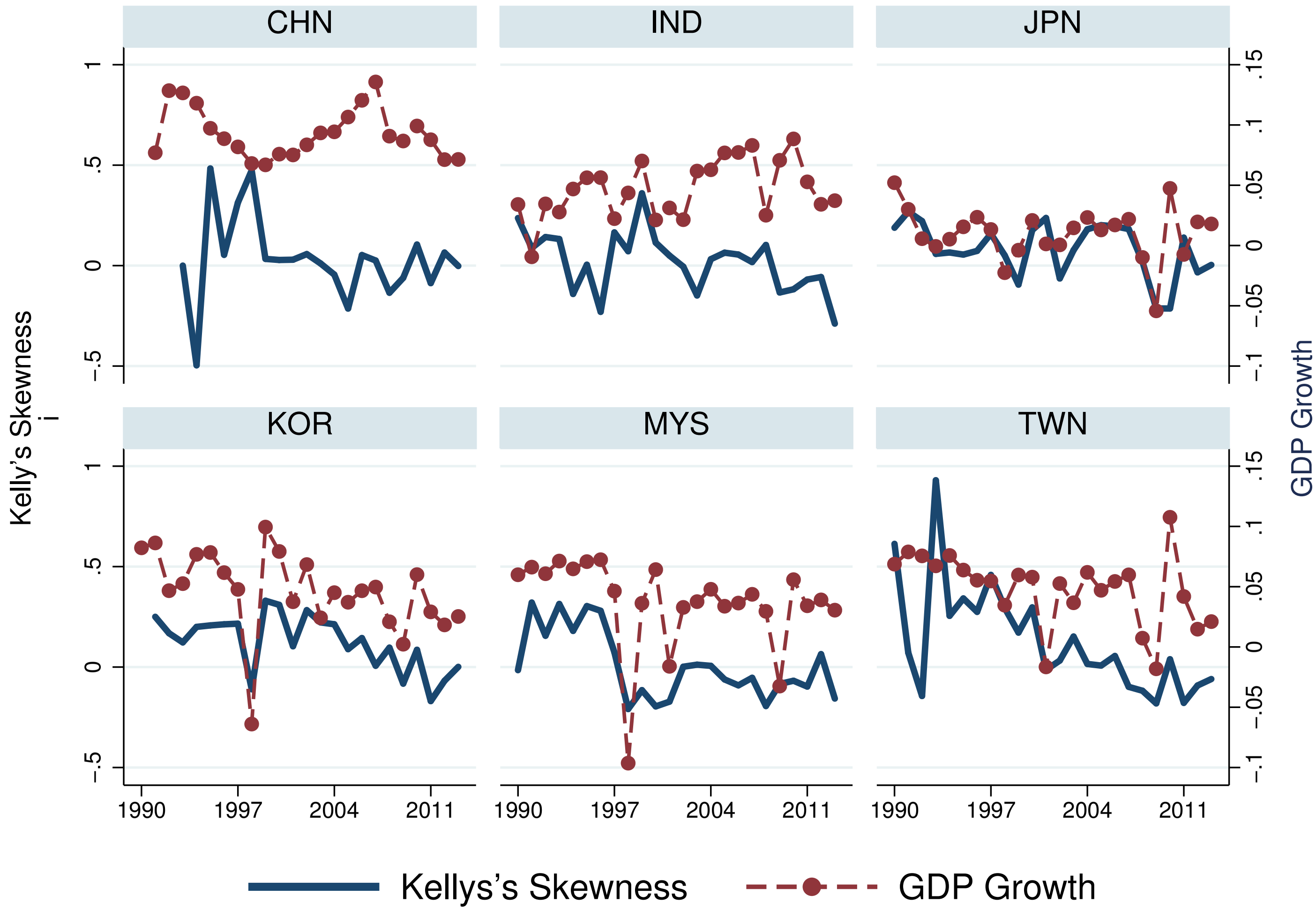

Figure 22 – Osiris: Dispersion and GDP Growth

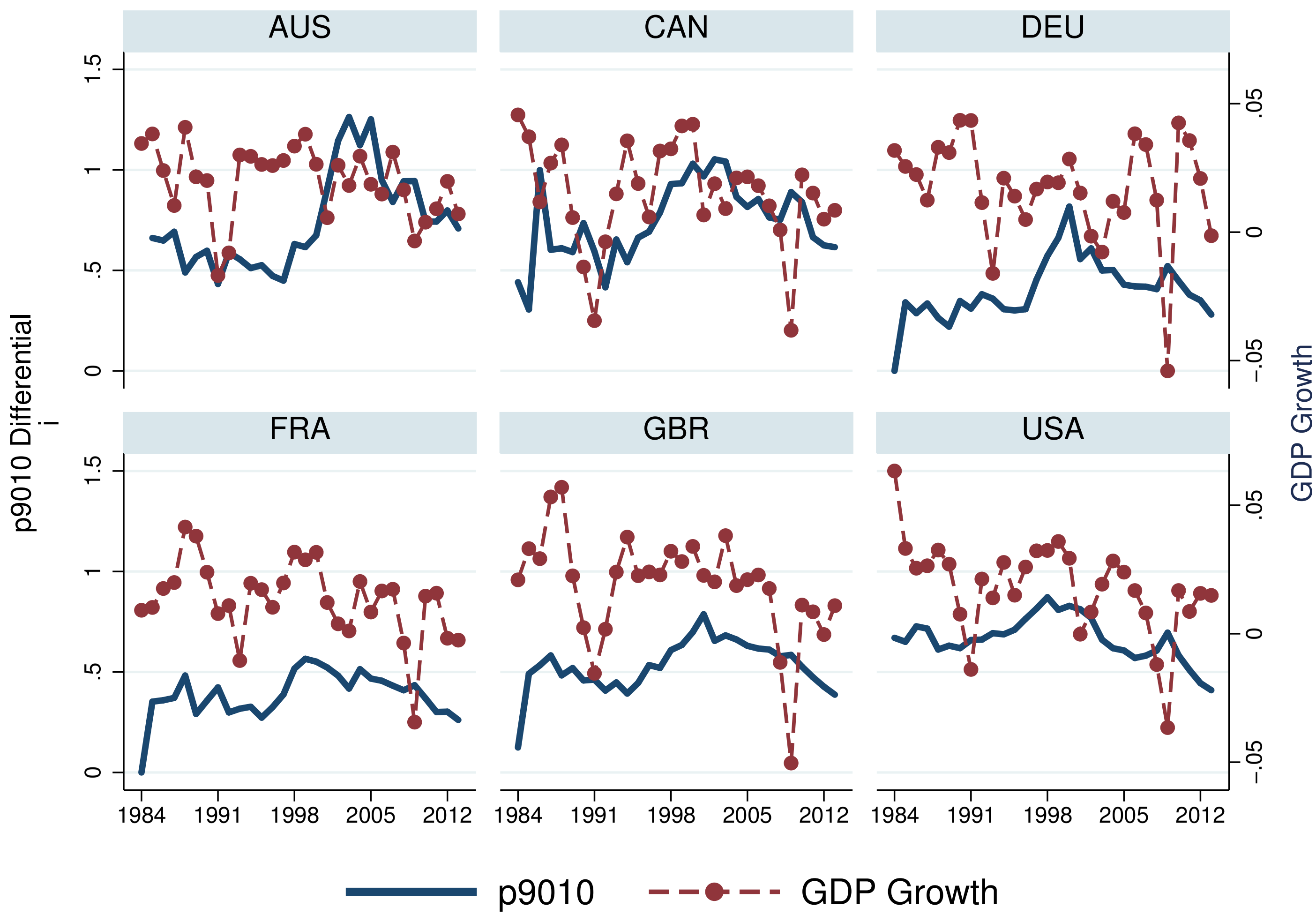

Figure 23 – Osiris: Dispersion and GDP Growth

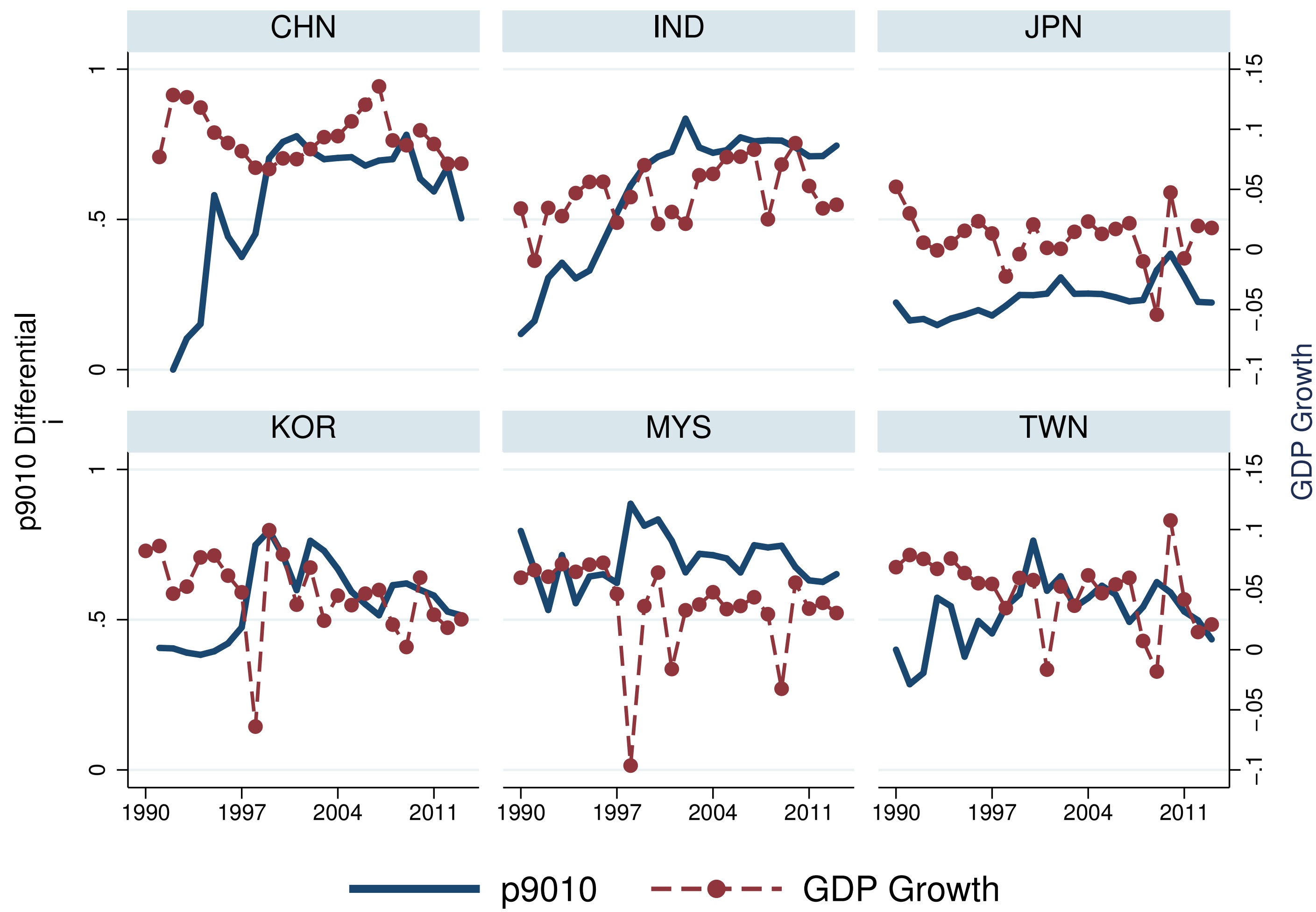

Figure 24 – Osiris: Upper and Lower Dispersion

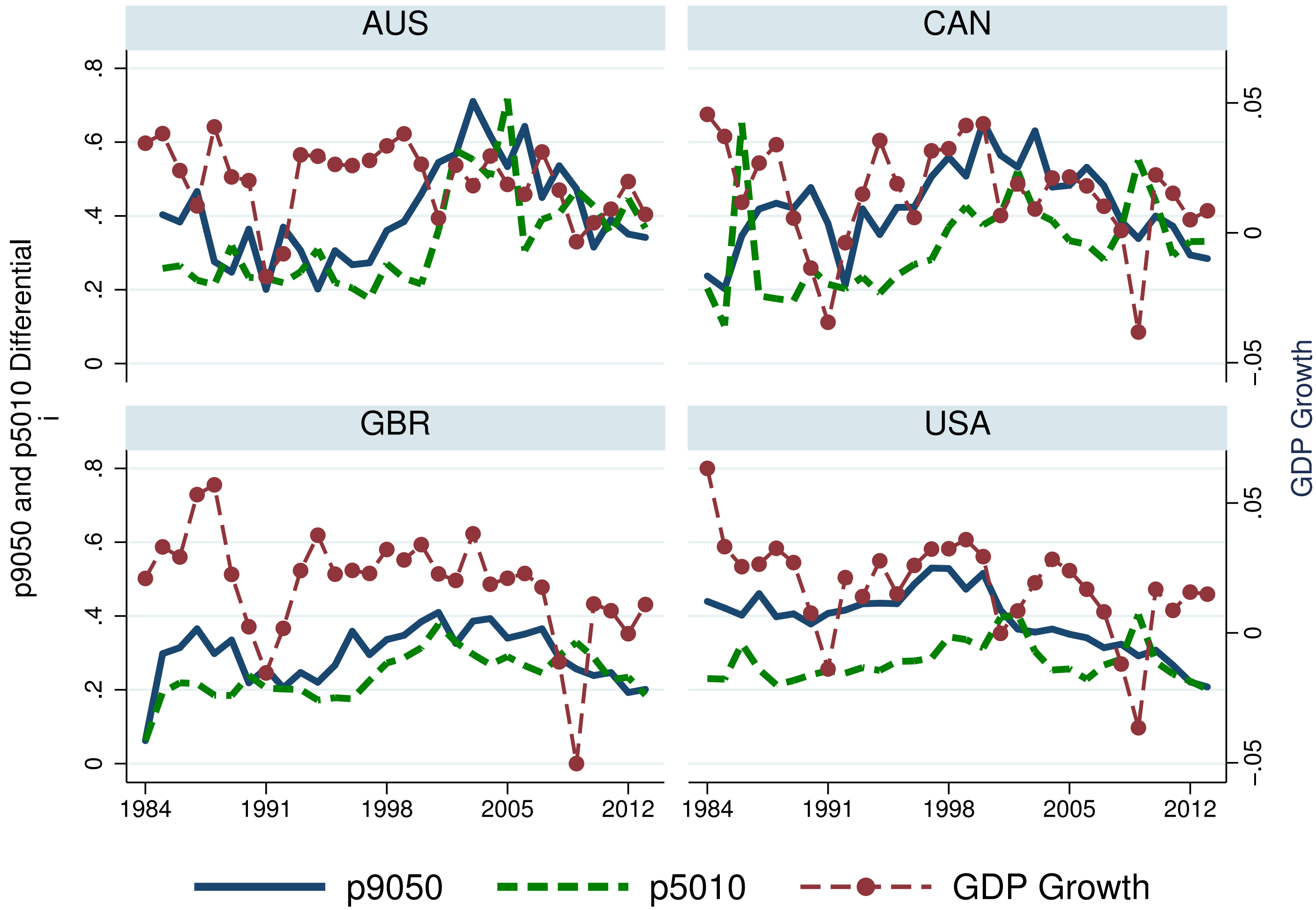

Figure 25 – Osiris: Upper and Lower Dispersion

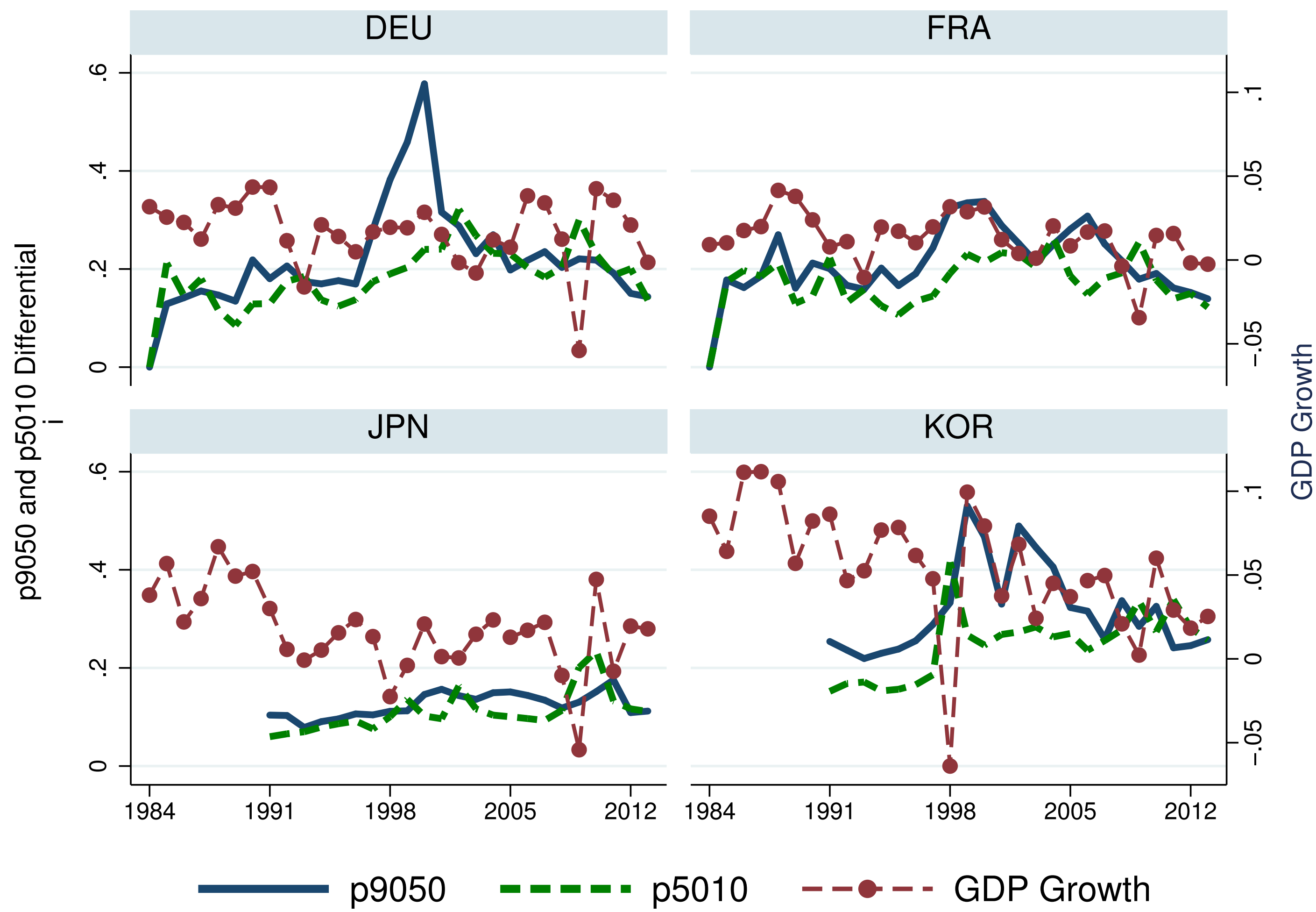

Figure 26 – Osiris: Upper and Lower Dispersion

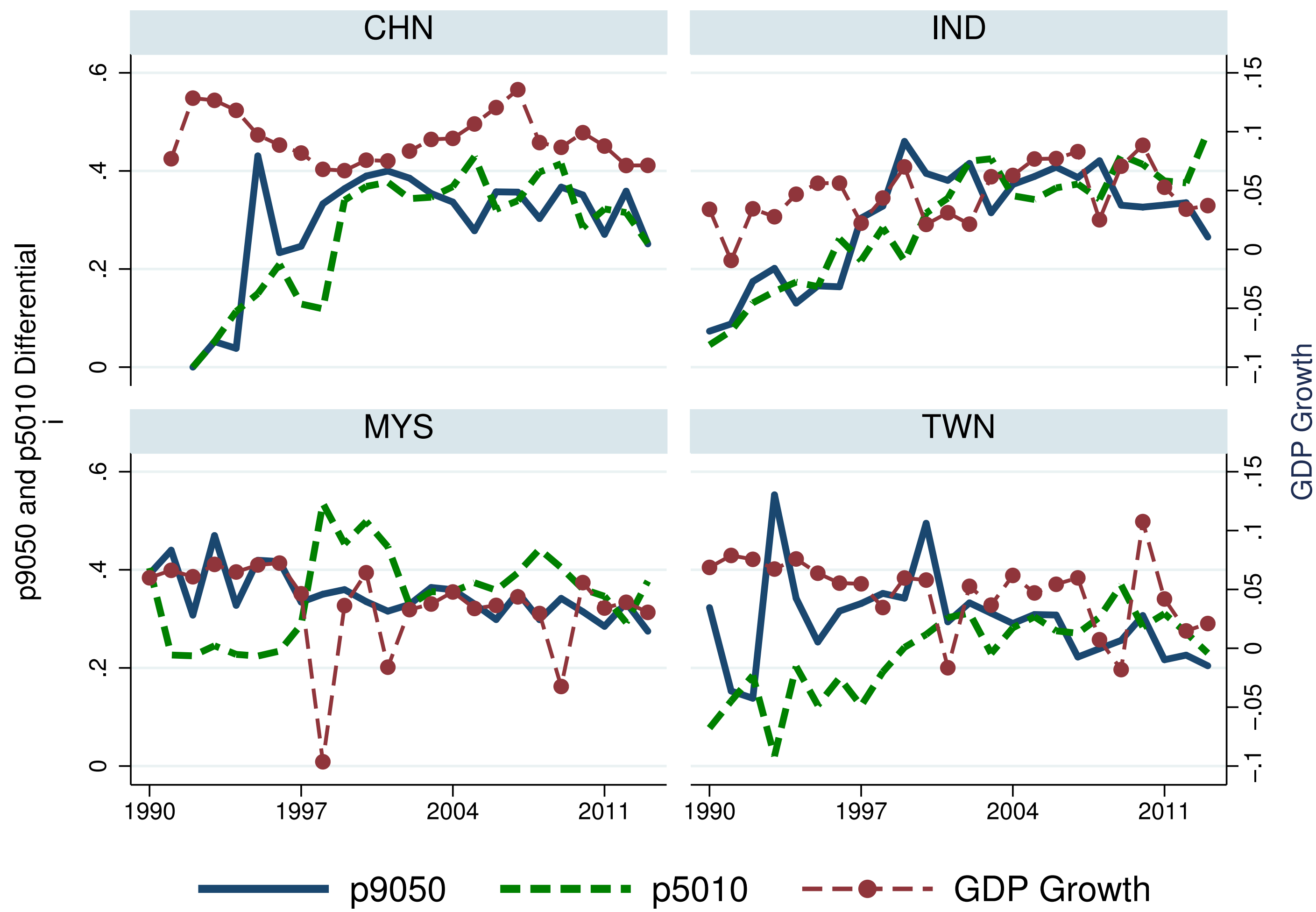

Figure 27 – Osiris: Cross Sectional Moments - European Union

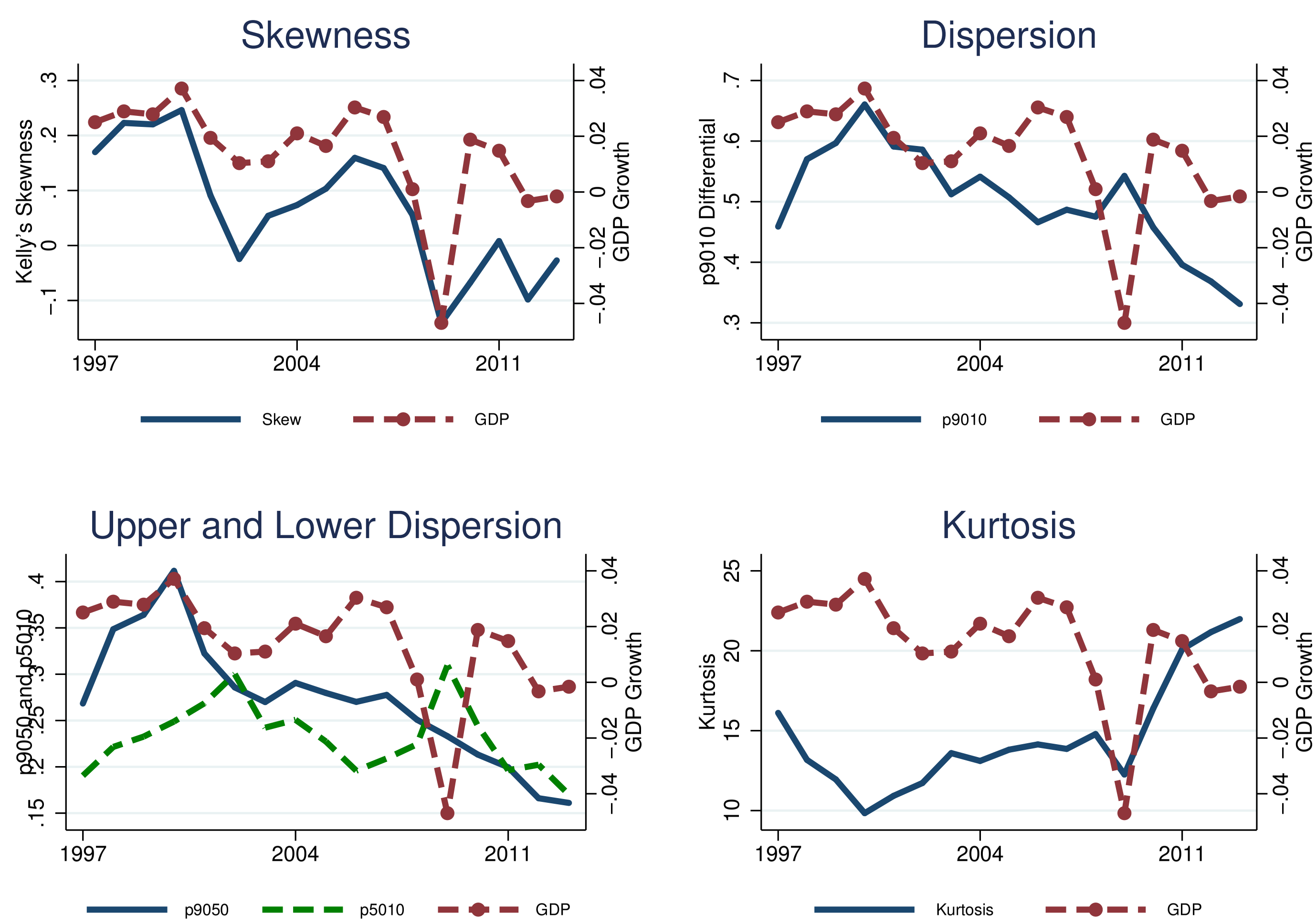

Figure 28 – Compustat Global: Skewness - Panel 1

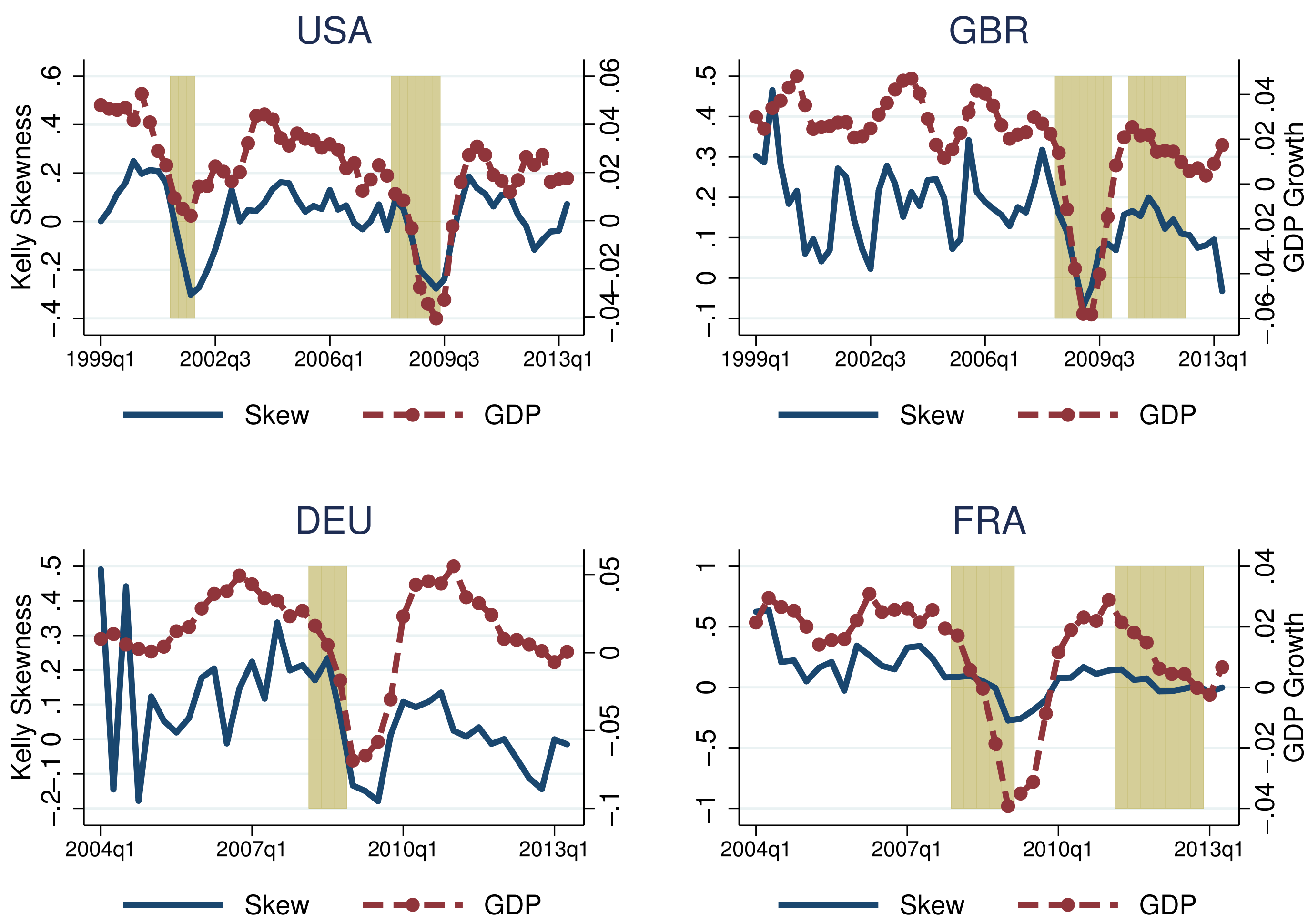

Figure 29 – Compustat Global: Skewness - Panel 2

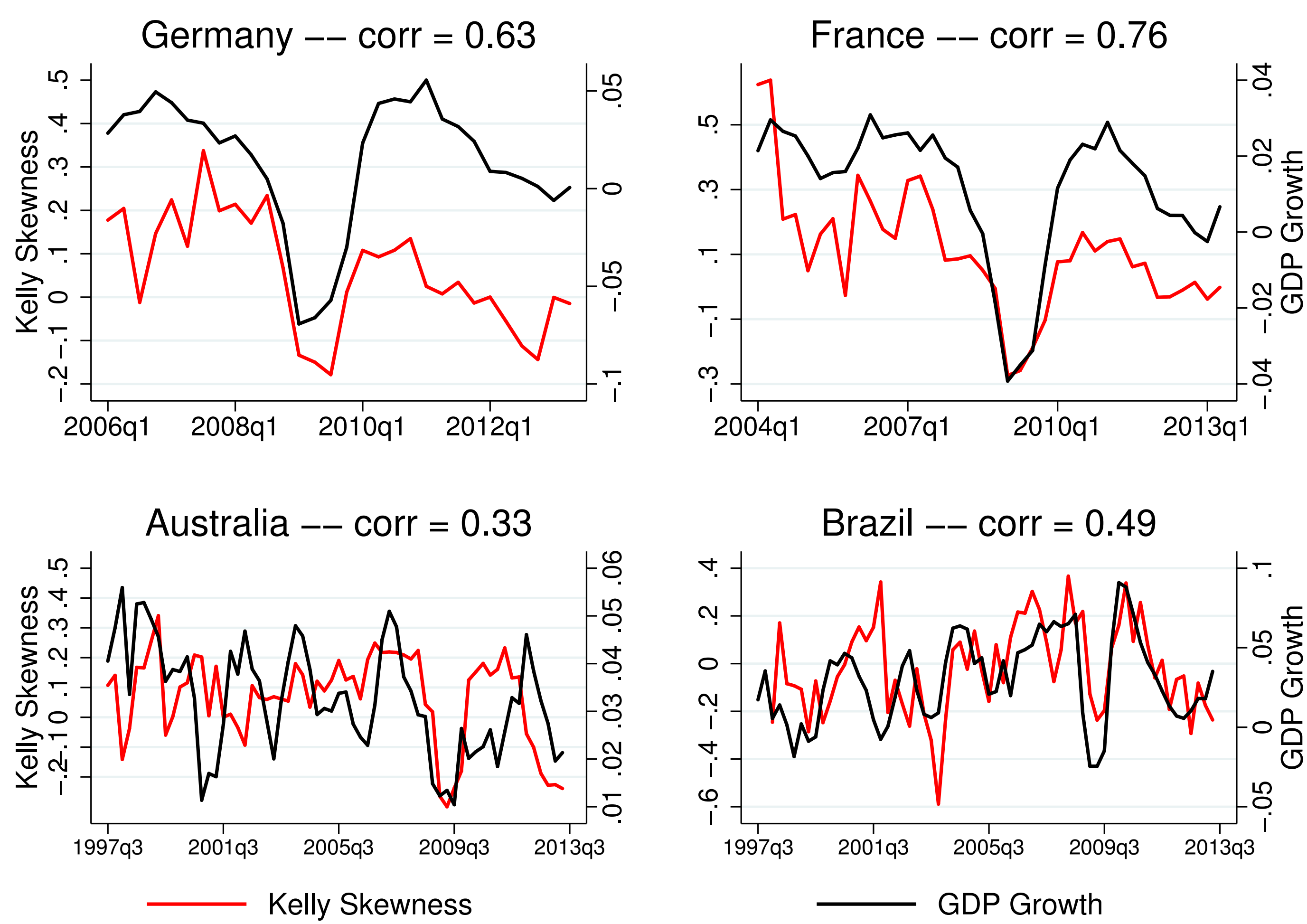

Figure 30 – Compustat Global: Skewness - Panel 1

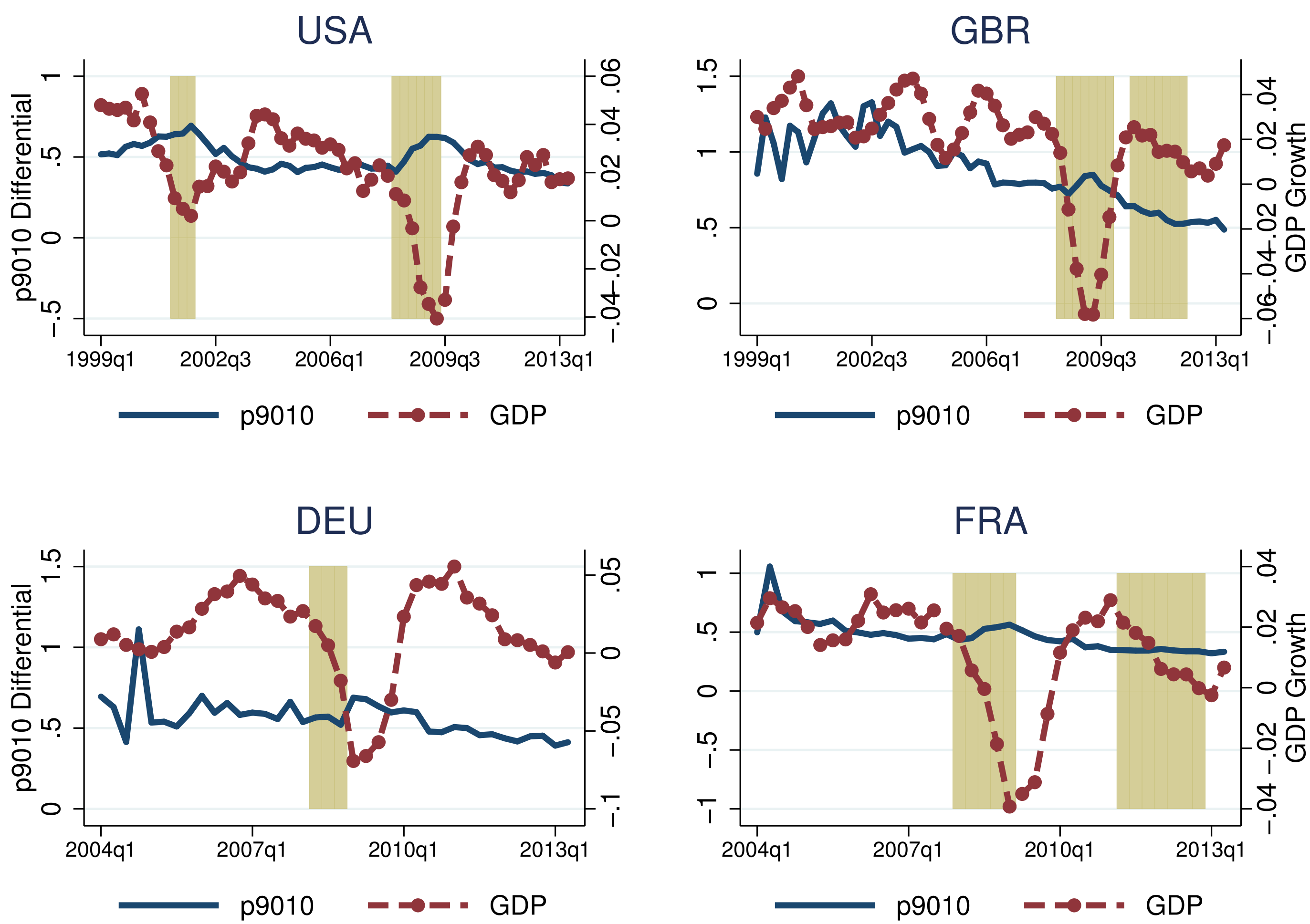

Figure 31 – Compustat Global: Dispersion - Panel 2

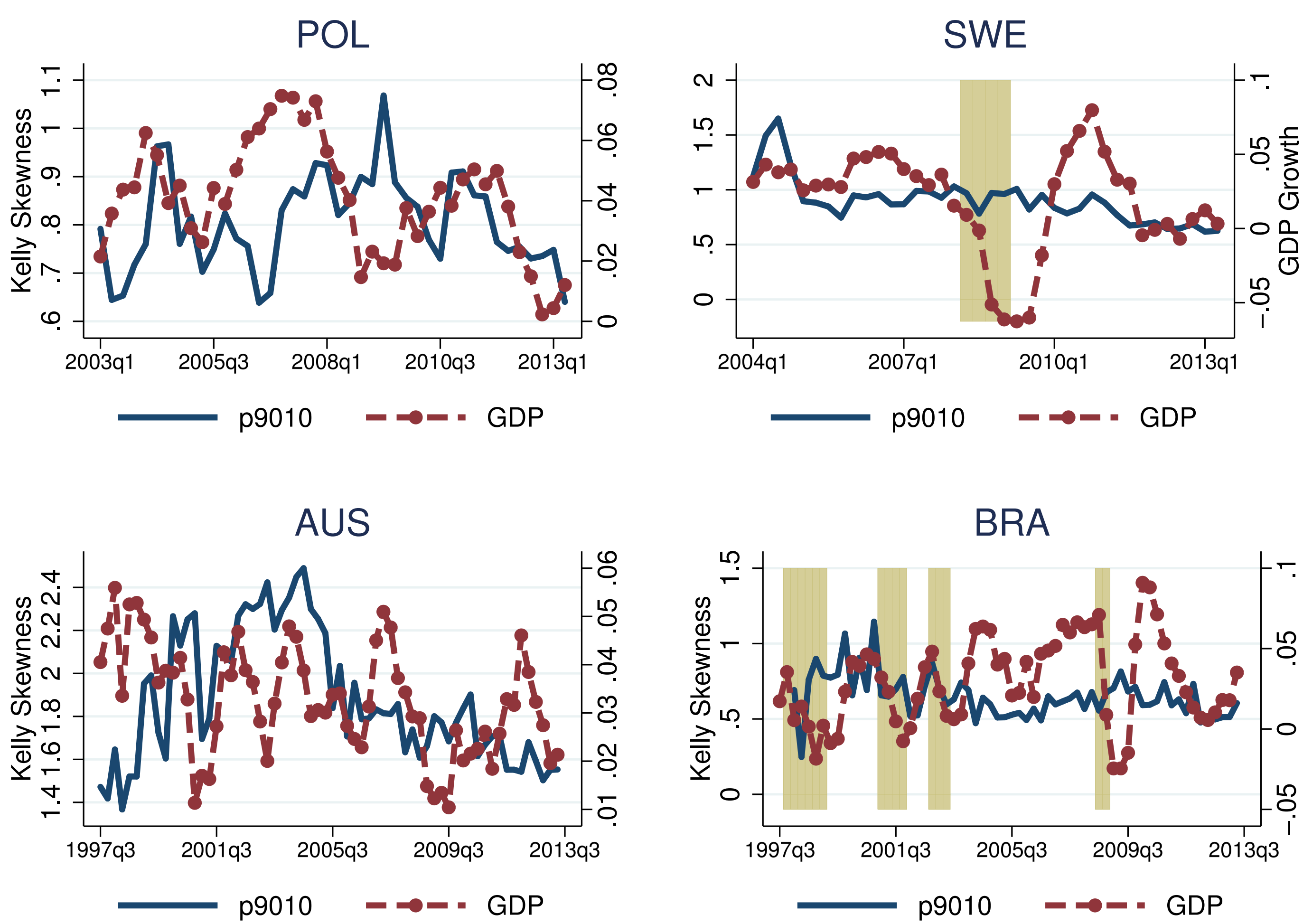

Figure 32 – Compustat Global: Cross Sectional Moments - European Firms

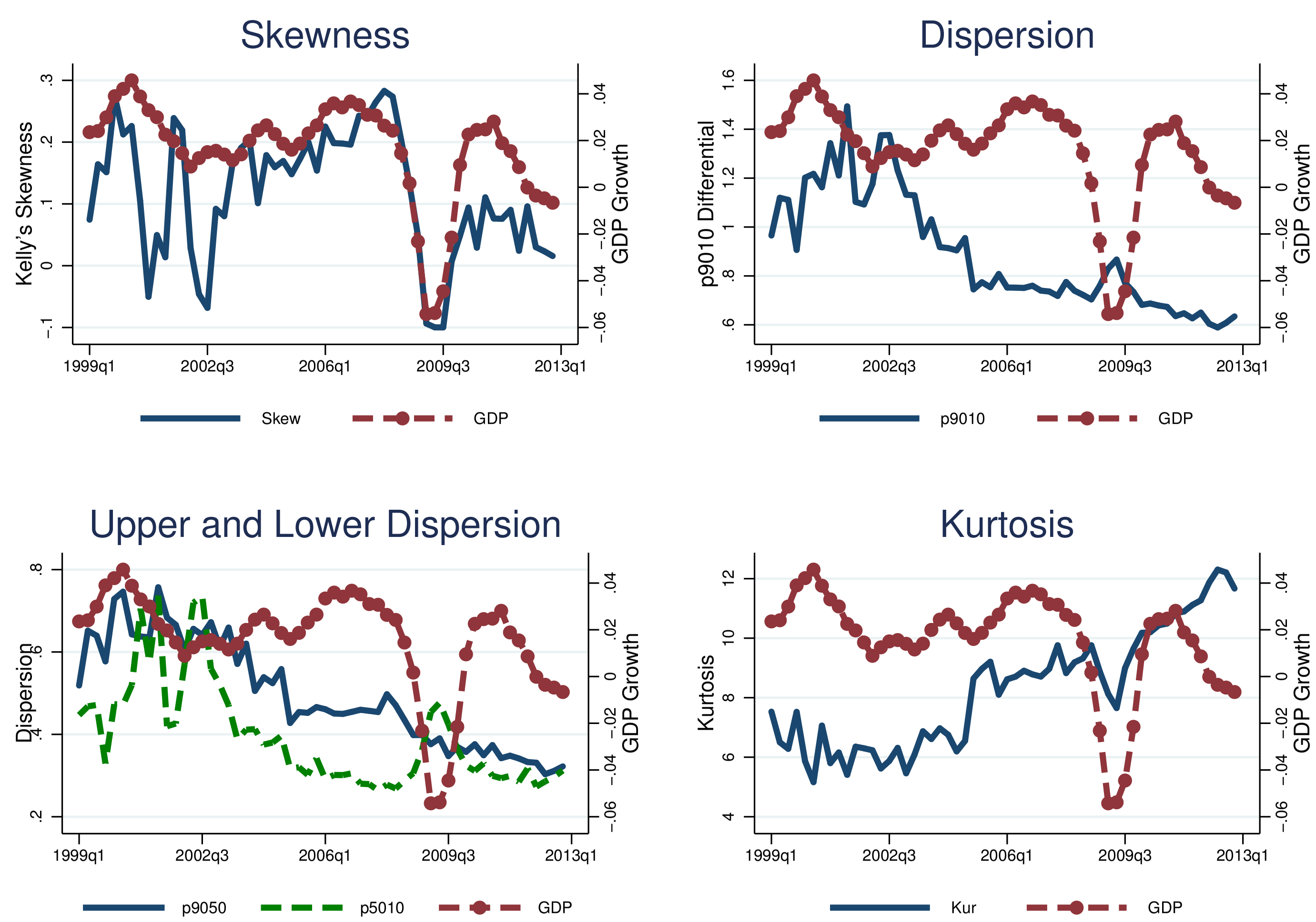

Figure 33 – Compustat Global: Distribution of Sales Growth Rates: Peak and Trough of the Great Recession

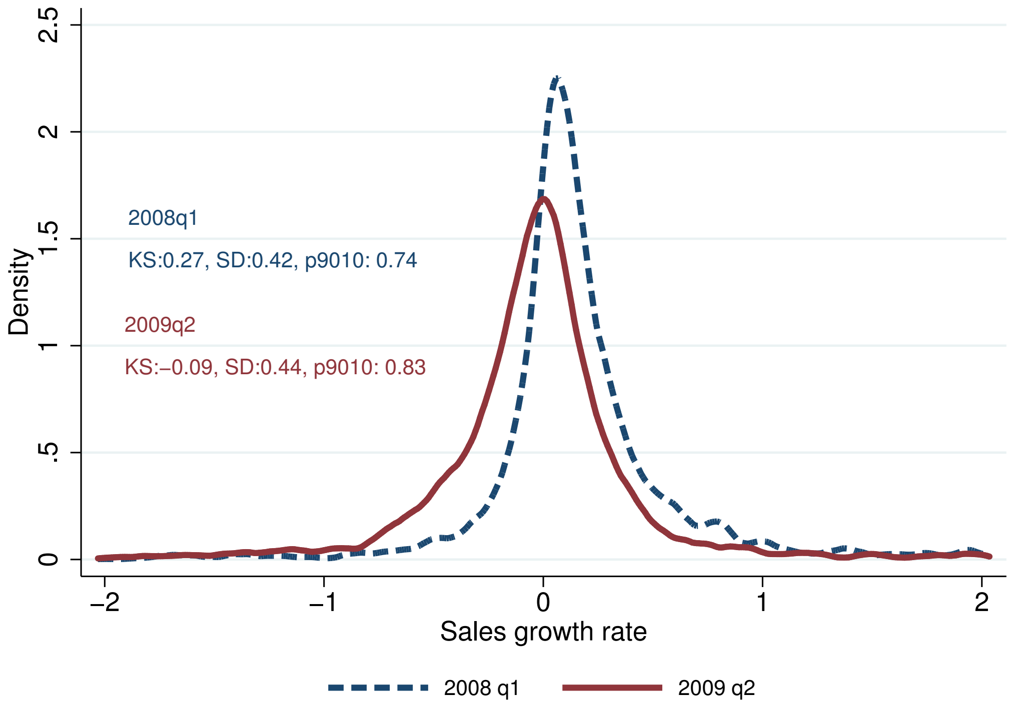

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Figure 34 – Compustat Global: Distribution of Sales Growth Rates: Years Before and During of the Great Recession

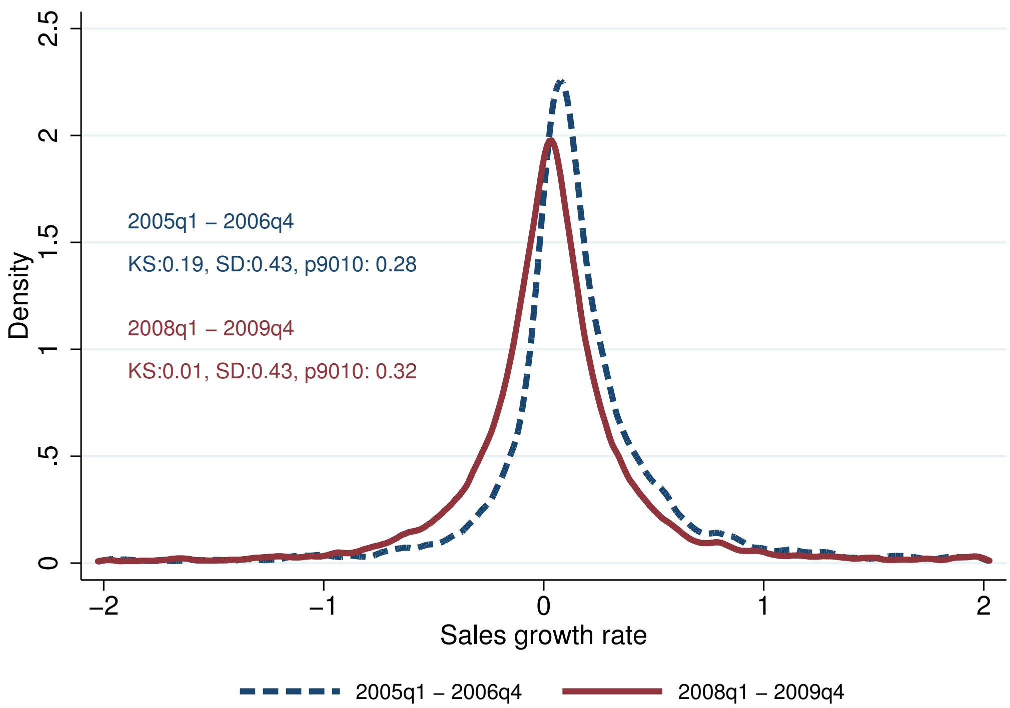

Figure 35 – Orbis: Skewness and GDP Growth - Set 1

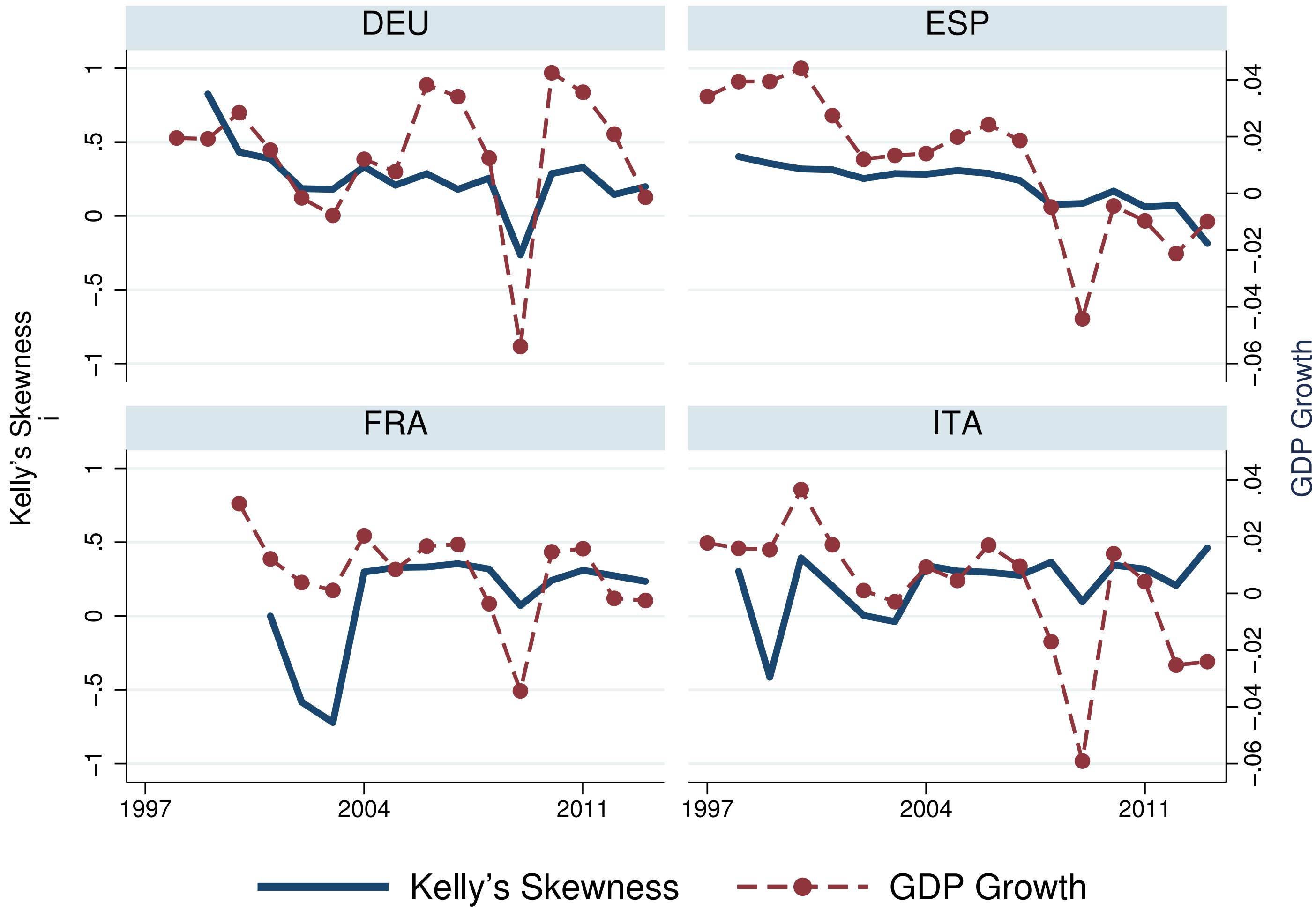

Figure 36 – Orbis: Skewness and GDP Growth - Set 2

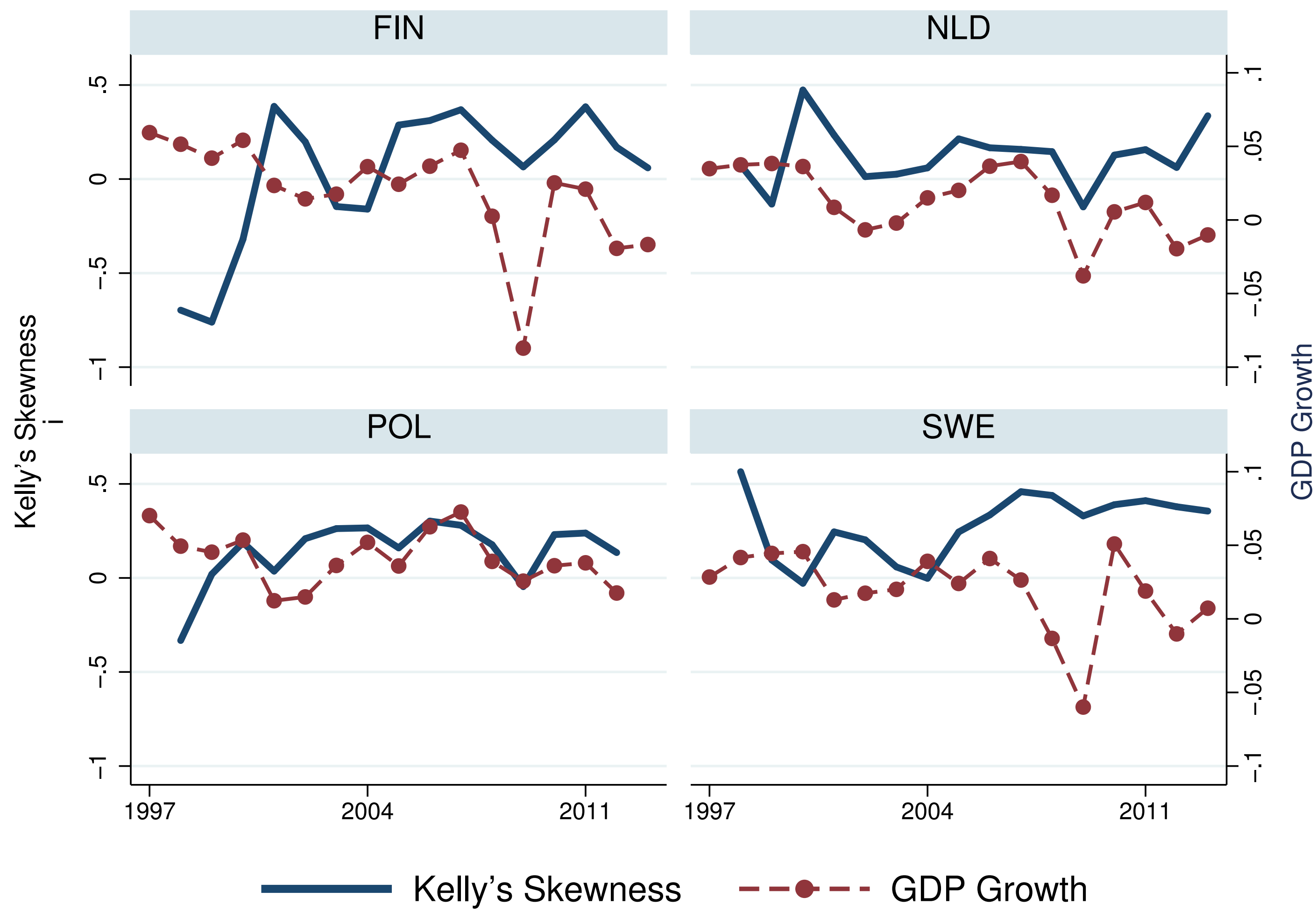

Figure 37 – Orbis: Dispersion and GDP Growth - Set 1

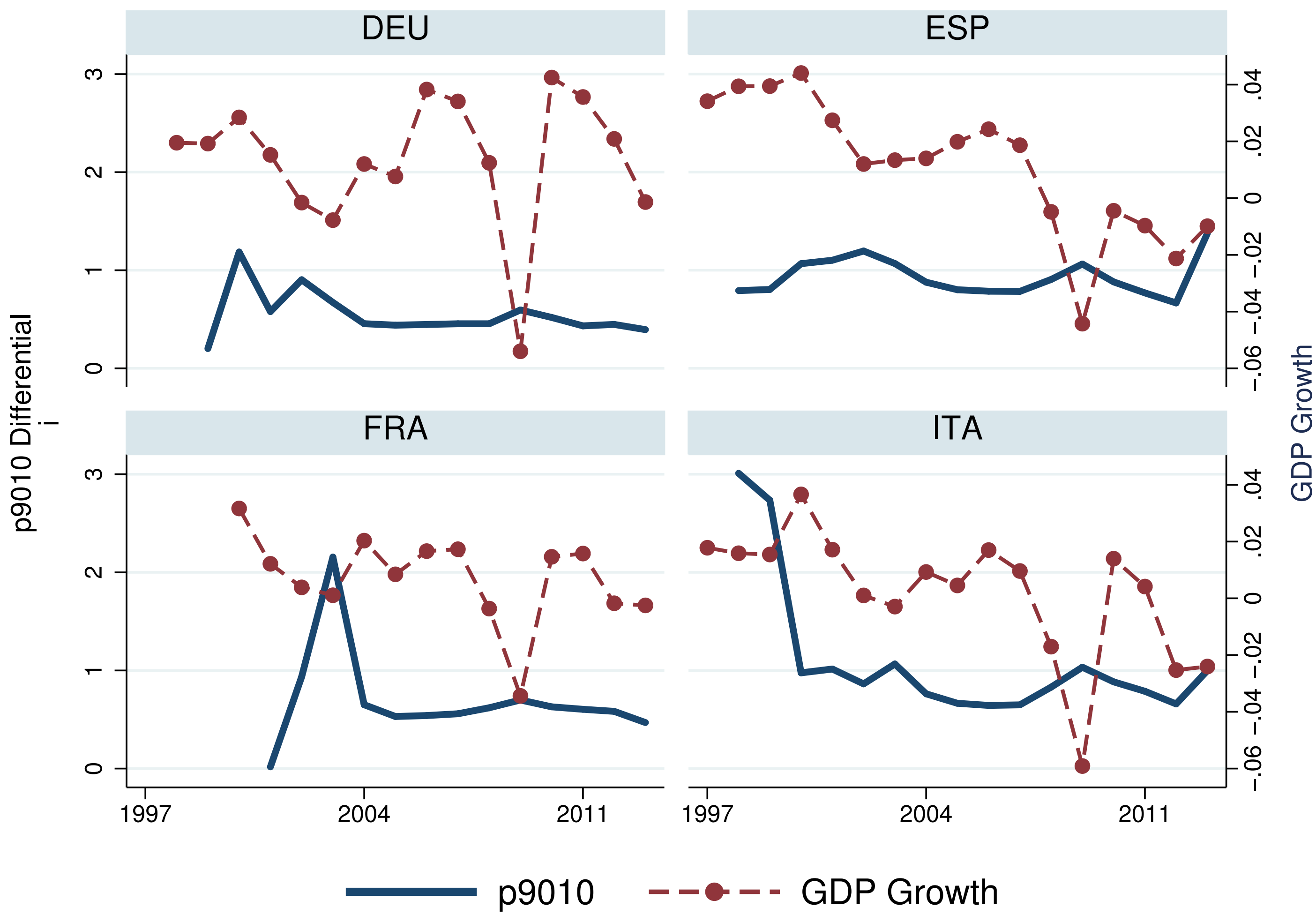

Figure 38 – Orbis: Dispersion and GDP Growth - Set 2

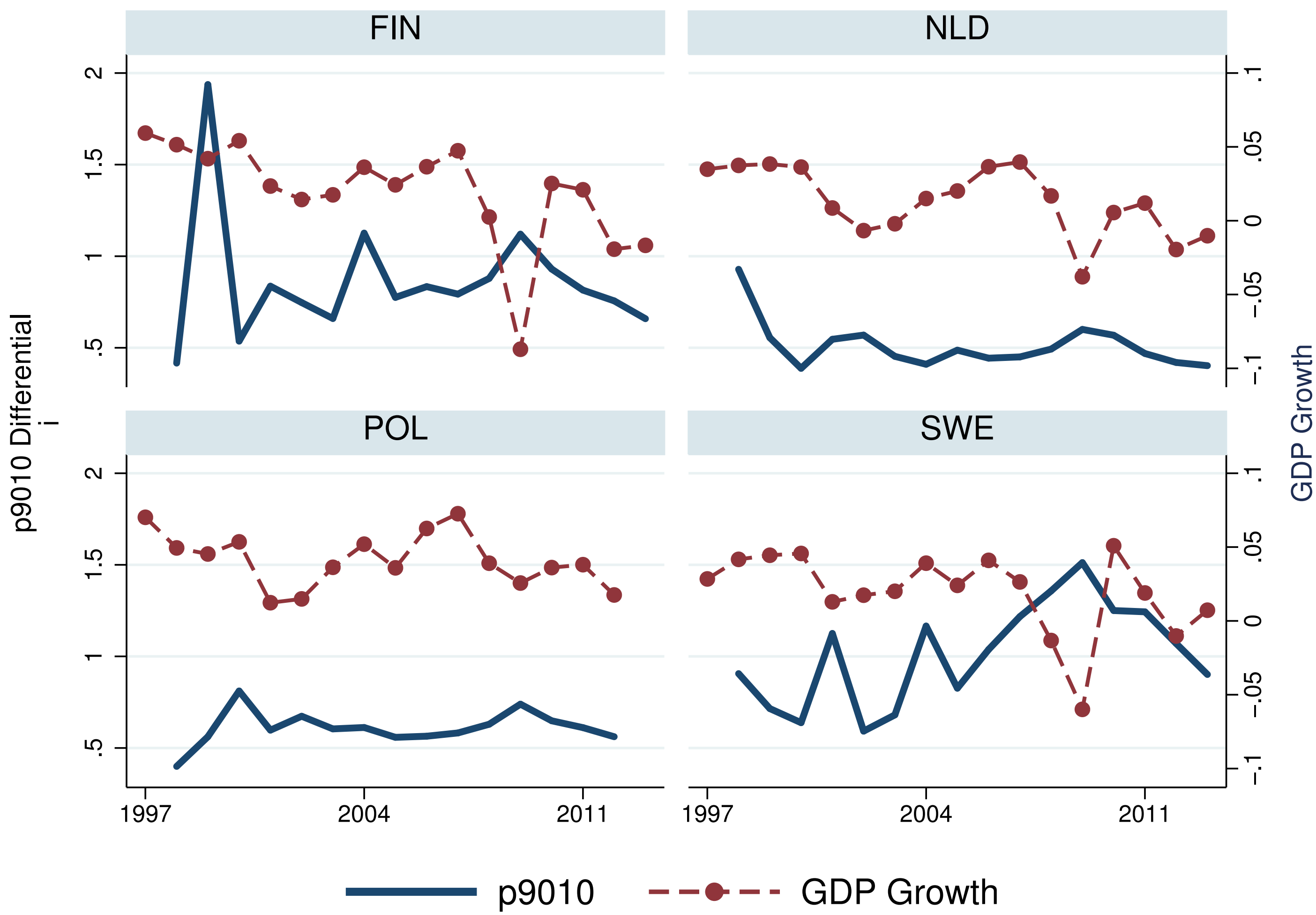

Figure 39 – Orbis: Upper and Lower Dispersion and GDP Growth - Set 1

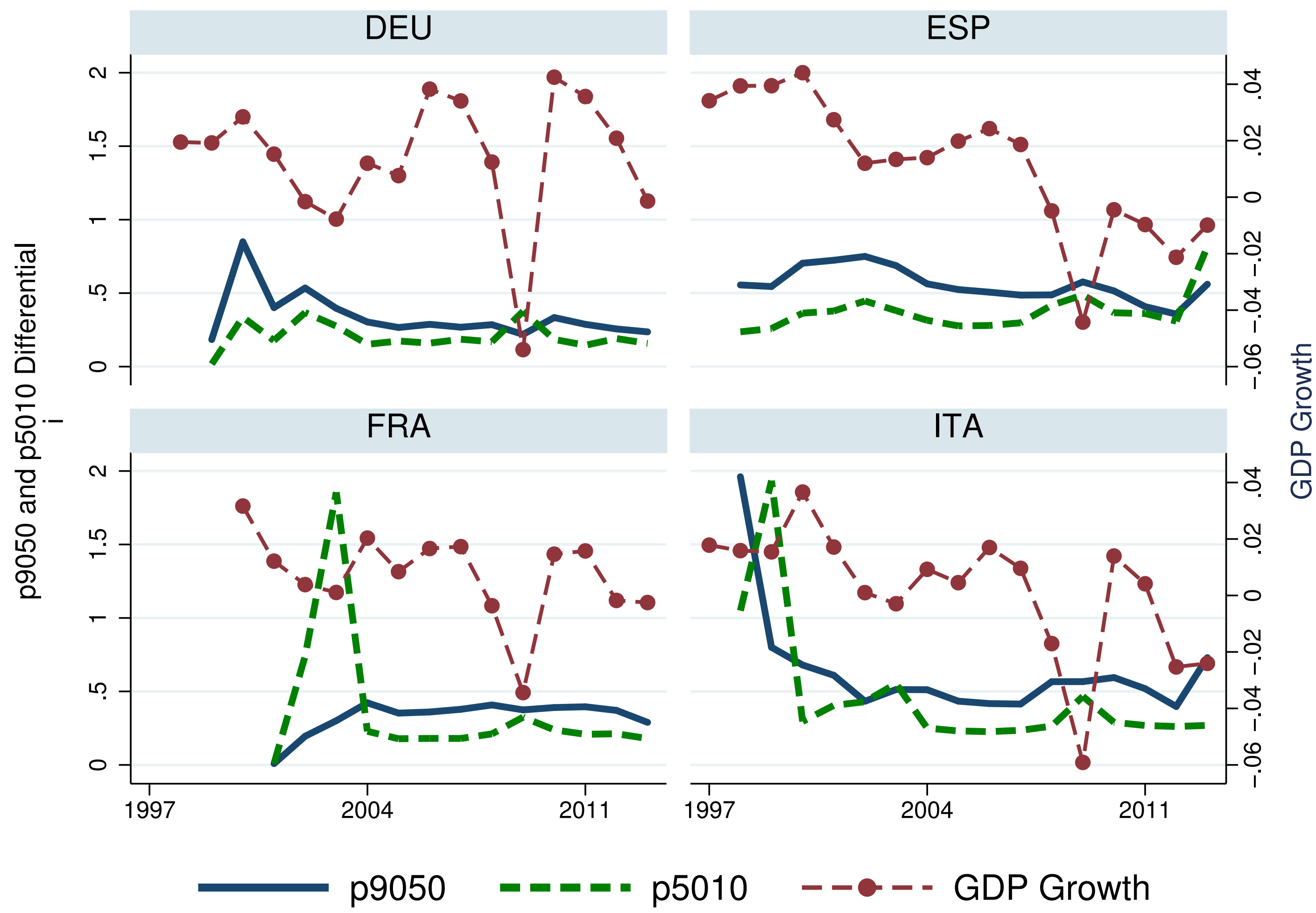

Figure 40 – Orbis: Upper and Lower Dispersion and GDP Growth - Set 2

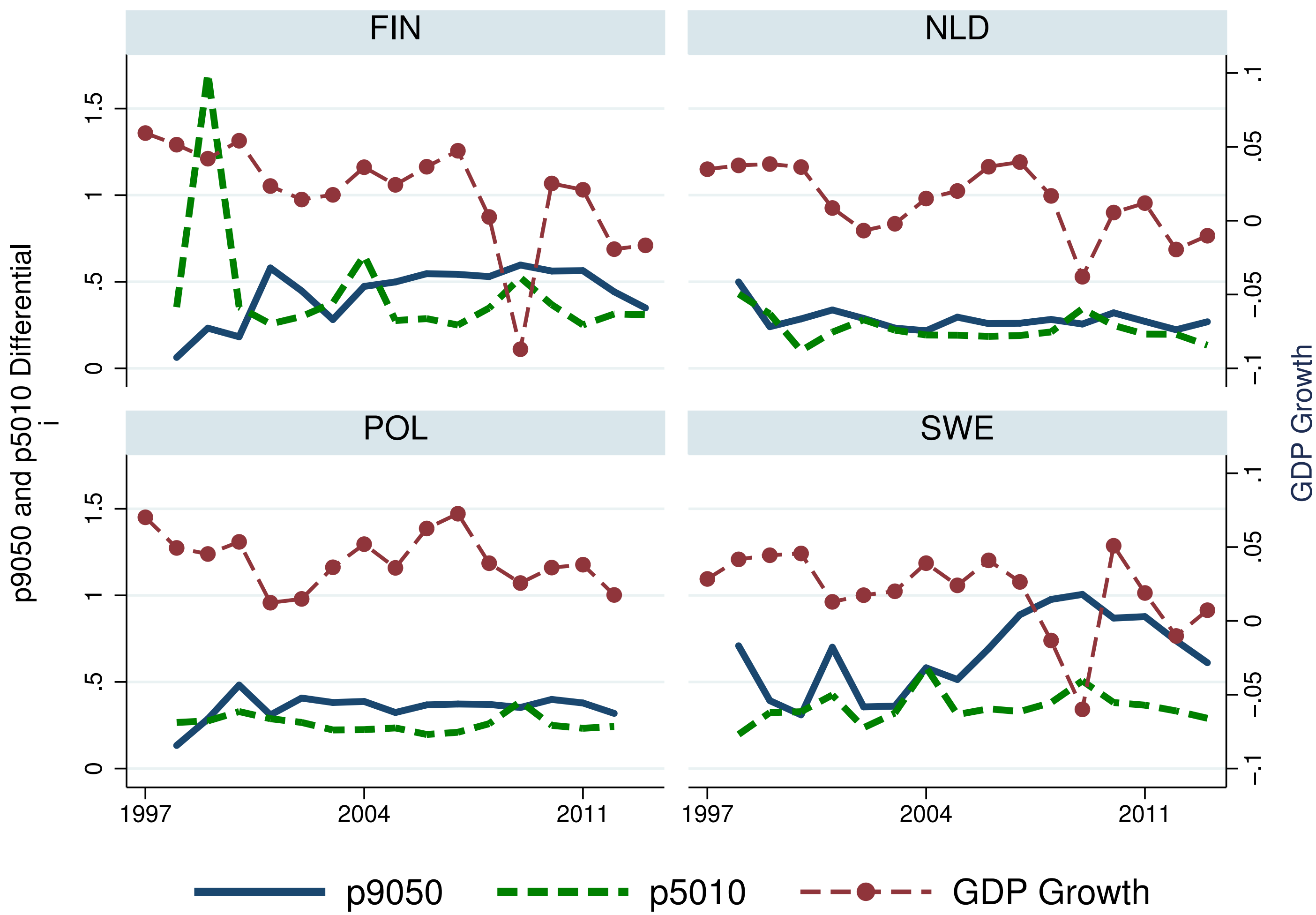

Figure 41 – Orbis: Cross Sectional Moment of European Firms

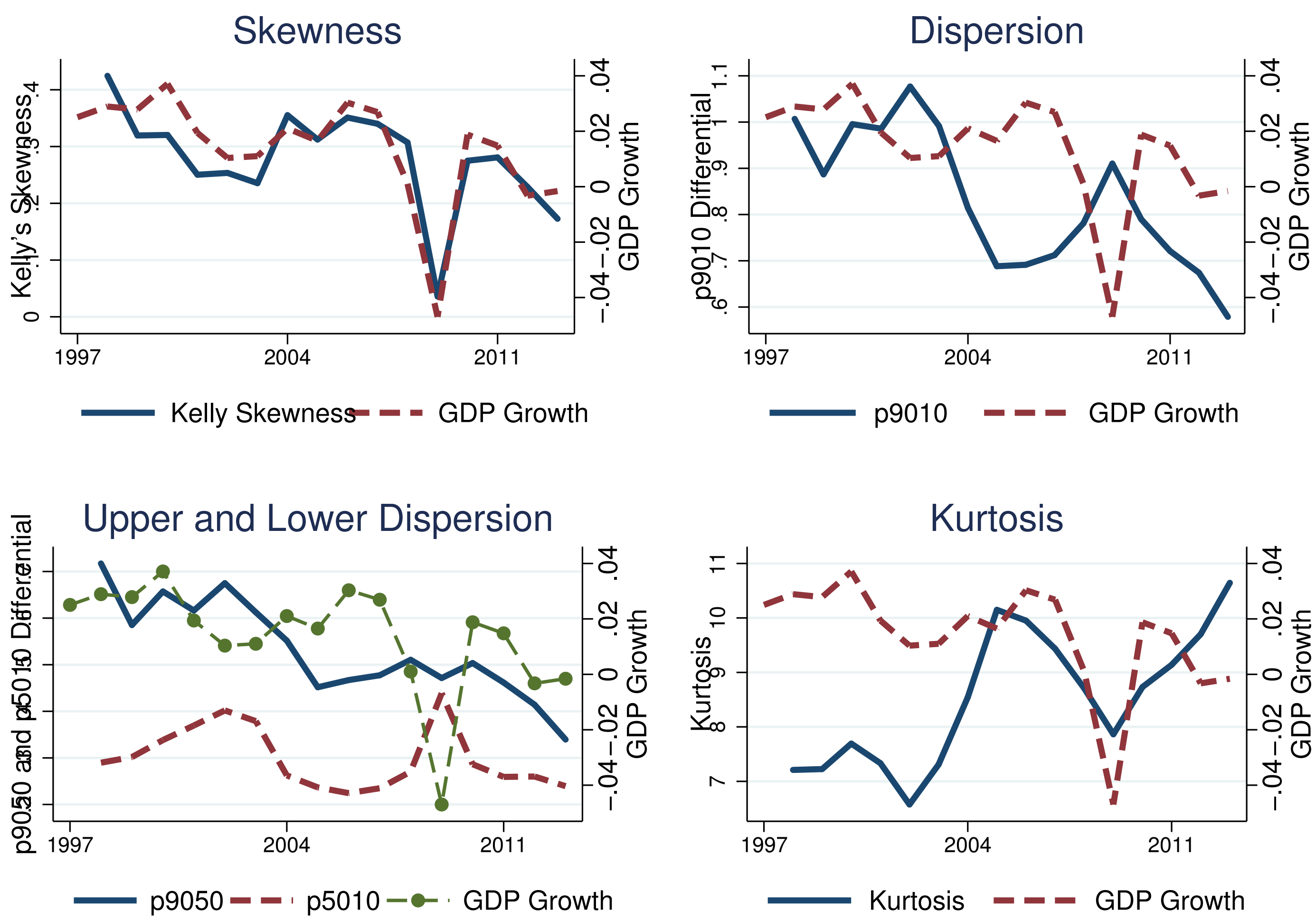

Figure 42 – Orbis: Distribution of Sales Growth Rates: Years Before and During of the Great Recession

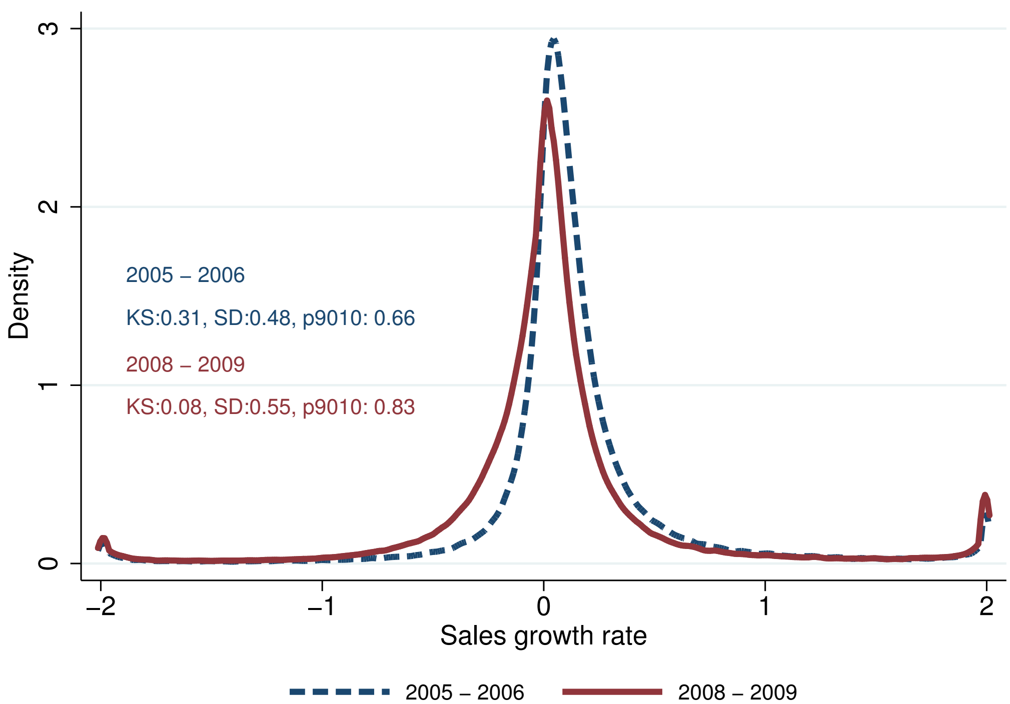

Figure 43 – Orbis: Cross Sectional Moment of European Firms