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By

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Volatility of national account data for Iceland and other OECD countries

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Abstract

In this paper we study volatility of national accounting aggregates for Iceland and compare it to volatility of these aggregates for other OECD countries. The paper uses three different methods to measure volatility: 1) log deviations from trend obtained using HP filter; 2) log deviations from trend obtained using the filter suggested by J.D. Hamilton; 3) log changes in the series. The paper studies effects of filters like seasonal adjustments on measured volatility. In most cases seasonal factors account for much of the variance in the unadjusted time series. Iceland and Ireland are outliers in this respect as seasonal variations explain relatively small part of the variance in the unadjusted series. We compare volatility of quarterly data to volatility of annual data and derive approximate formulas for the measures of volatility in annual data in terms of voltility and autocorrelations of the quarterly series. In most cases measured volatility in quarterly and annual data give similar pictures of the volatility of national accounting aggregates in a given country, but there are exceptions. Iceland is an outlier in this respect as the increase in the volatility of annual data for consumption is very large compared to volatility of seasonally adjusted data when log changes in the series are used to measure volatility. Much higher autocorrelations in the data for seasonally adjusted consumption compared to GDP explain why consumption can be less volatile than GDP in terms of seasonally adjusted quarterly data, but much more volatile in terms of annual data. We also study the relationship between the volatility of consumption and volatility of GDP. In almost half of the countries in our data set of 34 OECD countries consumption is more volatile than income measured by GDP. Finally, this paper studies the relationship between the size of an economy and its volatility and use it to assess if the Icelandic economy is more volatile than is to be expected when its size is taken into account.

JEL codes: E01, E30

Keywords: National account data, volatility, size of economies, quarterly and annual frequencies, OECD countries

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1. Introduction

The very small Icelandic economy has been characterized as being exceptionally volatile. Einarsson et al. (2016) note "the surprisingly high volatility of private consumption in Iceland", Einarsson et al. (2013) discuss "high volatility of economic activities in Iceland and Ireland", Daníelsson (2008) stresses that the variance of log changes in annual data for private consumption in Iceland is large, and much larger than the variance of log changes in GDP or Gross National Income (GNI), and Honjo and Hunt (2006) estimate efficiency frontiers for inflation and output gap volatility in Iceland, New Zealand, UK and Candada and find the distance of the frontier for Iceland from origo is roughly double the distance of the frontier for New Zealand, the second most volatile economy in their study. This leads them to question if the Icelandic authorities are able to vary the output gap as required to keep inflation within given boundaries.

In this paper we compare volatility in Iceland to volatility in 33 other OECD countries.[1] The data are for the period from the first quarter of 1995 to the fourth quarter of 2018, a period determined by the length of the time series for quarterly national accounts for the Icelandic economy published by Statistics Iceland. Thomson Reuter is the source of most of our data but data from Eurostat and Statistics Iceland are also used. We had to exclude some OECD countries as we were not able to obtain both seasonally adjusted and unadjusted official data for this period and for some countries the data period begins later than 1995Q1.

In this paper we will use three different methods to measure volatility: 1) standard deviation of log of the series divided by its trend obtained using HP filter; 2) standard deviation of log of the series divided by its trend obtained using the filter proposed by J.D. Hamilton; and 3) standard deviation of log changes in the series. In Section 2 we show that most of the time these different measures agree on the relative size of the volatility of a series, but there are notable exceptions.

If the volatility of GDP is measured by the standard deviation of log deviations of the unadjusted series from HP trend 9 countries are more volatile than Iceland. Sweden is e.g. more volatile than Iceland and in the 7th place, but New Zealand is in the 15th place out of 34. But if the seasonally adjusted series are used Iceland is in the 6th place, Sweden in the 16th and New Zealand in the 31st. This reflects that seasonal factors account for much more of the total variance of the unadjusted series for GDP in New Zealand (92%), and in Sweden (90%) than in Iceland (46%). The large differences in the contributions of the seasonal factors to the total variation in the series is discussed in Section 3.

It turns out that private consumption in Iceland is very volatile and more volatilve than GDP if we use log deviations from trend (HP or Hamilton) to measure volatily of unadjusted quarterly series, seasonally adjusted series and annual series, but if we use log changes in the seasonally adjusted series to measure volatility of private consumption in Iceland it is low, both compared to other economies and compared to volatility of GDP in Iceland. The reason why volatility of seasonally adjusted private consumption is much lower than volatility of seasonally adjusted GDP, while it is the other way around in the case of the unadjusted series, is that the seasonal factors explain much more of the total variance of the log changes in private consumption than they do for log changes in GDP. We also find when we measure voltility of annual data that standard deviation of log changes in private consumption is much larger than standard deviation of log changes in GDP. We find that this can be

[1] The 34 countries included are: Australia, Austria, Belgium, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, S. Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, UK, and USA.

explained in terms of much higher autocorrelations in the seasonally adjusted series for private consumption than in the seasonally adjusted series for GDP. Section 4 covers these issues.

The relative volatility of consumption compared to income has been central in economic theory. See e.g. Hall (1978), Christiano (1987), Cambell and Deaton (1989), Quah (1990). We find that volatility of consumption is larger than volatility of GDP in more than 40% of the economies in our sample. The papers focus on the volatility of seasonally adjusted data for the US where consumption is less volatile than GDP, but even in the case of the US, volatility of unadjusted series for consumption is considerably larger than volatility of unadjusted series for GDP when log changes in the series are used to measure volatility.

When comparing the volatility of private consumption and of GDP, Iceland is an outlier with very high ratio of volatility of private consumption compared to volatility of GDP. It is No. 1 when we use the Hamilton filter to estimate the trend for both seasonally adjusted and unadjusted series and also when log changes are used to measure volatility of annual data for GDP. When annual data are used and volatility measured using log deviations from trend the ratio of volatility of private consumption to volatility of GDP is highest in Australia, both when HP filter is used to estimate the trend and also when the Hamilton filter is used. But when volatility in annual data is measured using standard deviation of log changes this ratio is highest in Iceland. We discuss these issues in Section 5.

It seems intuitive that small economies are more volatile than larger economies which tend to be less open and therefore less vulnerable to international shocks and where the production structure is more diversified. Fuceri and Karras (2007) and Alouini and Hubert (2010) find that volatility declines with the size of the economy. We discuss this issue in Section 6 using our data set of 34 countries. We also look at a subsample where we exclude 10 countries that we consider less comparable to Iceland, and also clearly affect the estimated relationship between the size of the economy and volatility. We assess if the volatility of GDP in Iceland is large when the size of the economy is taken into account by comparing it to the estimated trend line. We find that even in the smaller sample there is a significant negative relationship between size of the economy and volatility. We also find that in most cases the volatility of GDP for Iceland is larger than what would be expected when taking the small size of the economy into account.

Finally, Section 7, concludes.

2. Different mehtods to measures volatility and the correlations of their outcomes

We assume that a time series X_t can be separated into trend and seasonal factors multiplicatively, i.e. we assume that

$$X_t = T_t \cdot C_t \cdot S_t \cdot I_t \tag{1}$$

where T_t is the trend, C_t cyclical factors, S_t seasonal factors, and I_t irregular factors.

The log deviation of the series from the trend is then:

$$\hat{X}_t = log(X_t) - log(T_t) = log(C_t) + log(S_t) + log(I_t) \tag{2}$$

The seasonally adjusted seris, X_t^{sa}, is defined by $X_t = S_t X_t^{sa}$ and the log deviation of the series from the trend is:

$$\hat{X}_t^{sa} = \hat{X}_t - log(S_t) = log(C_t) + log(I_t) \tag{2'}$$

Differencing gives:

$$Dlog(X_t) = Dlog(X_t^{sa}) + Dlog(S_t) \tag{3}$$

The seasonal factors are the differences between these two series. We then estimate the trend from the official seasonally adjusted quarterly data using alternatively HP filter with $\lambda = 1600$, the standard value for quarterly series, and the filter proposed by Hamilton (2017). It is to be expected that these estimates of the trend are somewhat different from the estimates made by the statistical offices as part of their estimation of the seasonally adjusted series. Our finding that the correlations beween the seasonal factors estimated by the statistical officies and deviations of seasonally adjusted series from the trends that we estimate is insignificant in almost all cases indicates that this problem does not seriously affect our results.

We use the trends obtained from the seasonally adjusted series to calculate log deviations of both the seasonally adjusted and the unadjusted series. The trend for the annual data is simply the sum of the values for the four quarters in the calendar years.

Figure 1

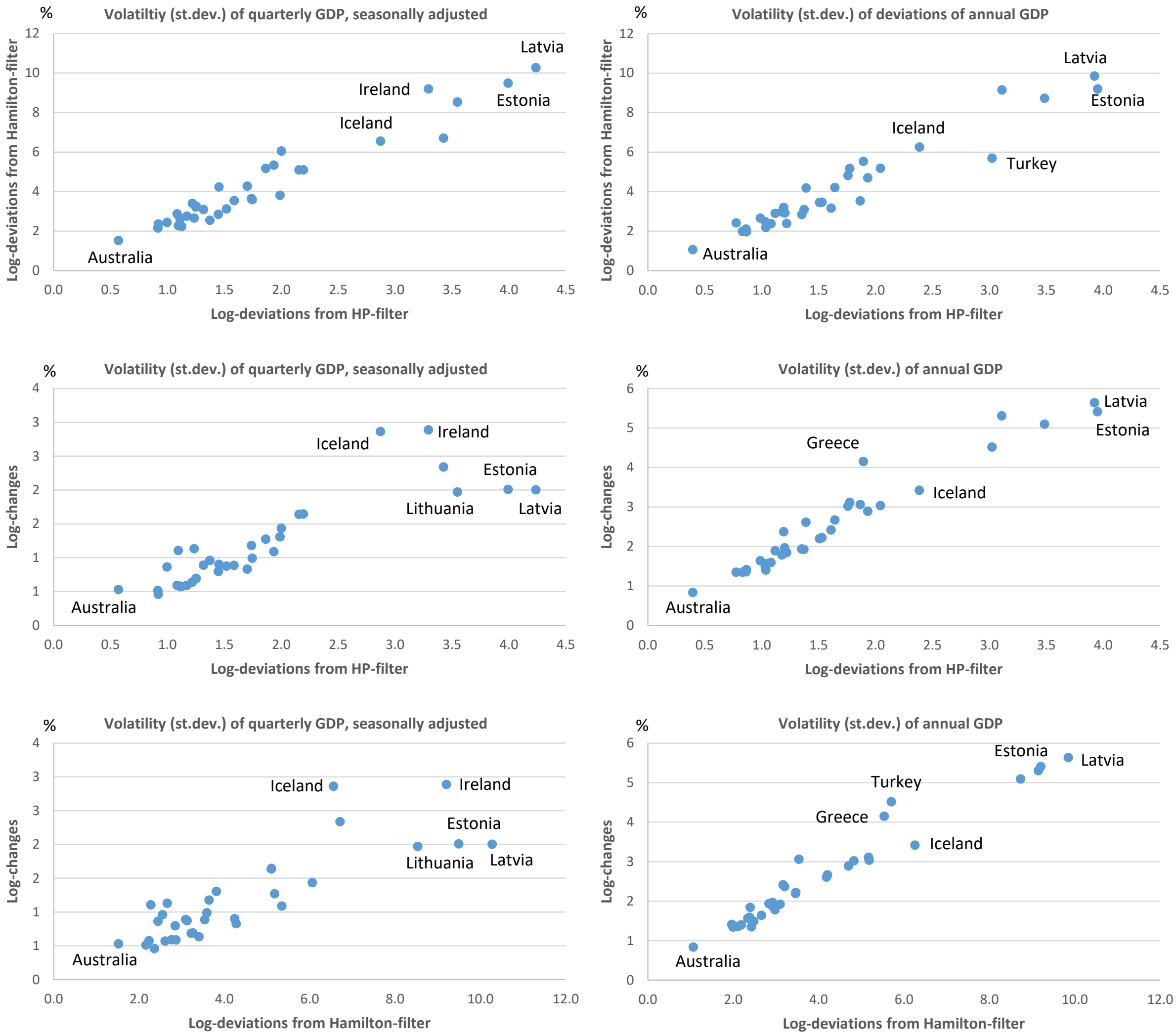


Figure 1 shows scattergrams for the three measures of volatility, two in each figure. The volatility of seasonally adjusted quarterly data are shown in the figures to the left while volatility of annual data are shown in figures to the right.

Table 1 shows the estimated correlations between the different estimates of volatility for the 34 countries in our sample.

Table 1

Correlation matrix

Volatility of GDP, quarterly data, adjusted

	HP	Hamilton	Changes
HP	1.00	0.97	0.87
Hamilton	0.97	1.00	0.85
Changes	0.87	0.85	1.00

The correlations are higher in the case of annual data as shown in Table 2

Table 2

Correlation matrix

Volatility of GDP, annual data

	HP	Hamilton	Changes
HP	1.00	0.97	0.97
Hamilton	0.97	1.00	0.97
Changes	0.97	0.97	1.00

For volatility of the unadjusted quarterly GDP series the correlations are lower than in Table 1. For our data set the correlations are larger than in Table 1 in the case of measurements of the volatility of seasonally adjusted consumption.

3. Volatility of seasonally adjusted and unadjusted data

It follows from Equation (2‘) above that for deviations from trend ($\hat{X}_t$) we have that:

$$Var(\hat{X}_t) = Var(\hat{X}_t^{sa} + S_t) = Var(\hat{X}_t^{sa}) + Var(S_t) + 2 \cdot Cov(\hat{X}_t^{sa}, S_t) \quad (4)$$

and in the same way it follows from Equation (3) that for log changes we have that:

$$Var\left(Dlog(\hat{X}_t)\right) = Var\left(Dlog(\hat{X}_t^{sa}) + Dlog(S_t)\right)$$

$$= Var\left(Dlog(\hat{X}_t^{sa})\right) + Var\big(Dlog(S_t)\big) + 2 \cdot Cov\left(Dlog(\hat{X}_t^{sa}), Dlog(S_t)\right) \quad (5)$$

i.e. the variance in the unadjusted series can be decompsed into the variance of the seasonally adjusted series, the variance of the seasonal factors and two times the covariance of these variables. The first part of Table 3 (first four columns) shows volatility of the unadjusted data for GDP, and volatility of the seasonally adjusted data. The second part (next three columns) shows the relative contributions of terms on the right side of Equation (4) to the variance of the unadjusted series.

In Table 3 volatility is measured using log deviations from HP trend. The table also contains data on the volatility of the annual series measured by the standard deviation of annual data from the trend obtained by summing the four quarters of the estimated trend for the quarterly data. The standard deviations calculated to measure the volatility have been multiplied by 100, which is indicated by the symbol %.

Table 3

	Standard deviation of log deviations of GDP from HP trend									
					Contribution to the variance					Annual/
	Quarterly data (%)				**of the unadj. series (%)**			**Annual data (%)**		seas.adj.
	Unadj.		S. adj.		S. adj.	Seas.	2*Co-			quarterly
	series	Rank	series	Rank	series	factors	variance	St.dev	Rank	st.dev.
Australia	3.02	19	0.57	34	3.6	96.0	1.0	0.39	34	0.69
Austria	2.85	20	1.17	26	16.8	82.6	1.1	1.08	25	0.92
Belgium	3.02	18	0.92	33	9.2	90.9	-0.2	0.83	32	0.91
Chile	3.17	17	1.74	13	30.2	68.5	2.5	1.53	15	0.88
Czech R.	3.93	12	1.70	15	18.7	81.0	0.5	1.64	13	0.96
Denmark	2.46	26	1.32	21	28.7	71.5	-0.3	1.18	23	0.89
Estonia	5.44	5	3.99	2	53.9	43.8	4.5	3.95	1	0.99
Finland	3.85	13	1.86	12	23.5	73.3	6.4	1.76	12	0.94
France	1.79	33	0.92	32	26.2	73.6	0.4	0.86	31	0.94
Germany	1.93	29	1.45	19	56.4	41.0	5.2	1.35	19	0.93
Greece	4.88	8	2.00	9	16.8	79.9	6.6	1.89	9	0.95
Hungary	5.43	6	1.45	18	7.2	90.3	5.1	1.39	17	0.96
Iceland	4.00	10	2.87	6	51.4	45.9	5.2	2.38	6	0.83
Ireland	3.70	14	3.29	5	79.2	18.7	4.2	3.11	4	0.94
Israel	1.85	32	1.52	17	67.7	26.8	10.8	1.37	18	0.90
Italy	2.66	24	1.25	22	22.1	75.8	4.1	1.12	24	0.89
Japan	2.57	25	1.37	20	28.5	67.3	8.3	1.22	20	0.89
S. Korea	3.99	11	1.99	10	24.9	69.9	10.4	1.87	10	0.94
Latvia	7.93	2	4.24	1	28.5	70.8	1.3	3.92	2	0.93
Lithuania	7.06	3	3.55	3	25.2	71.1	7.4	3.48	3	0.98
Luxemburg	2.72	22	2.16	8	63.0	36.1	1.8	1.93	8	0.90
Mexico	2.33	28	1.74	14	55.8	41.7	5.0	1.61	14	0.93
Netherlands	2.36	27	1.25	23	27.9	71.2	1.9	1.20	21	0.96
New Zealand	3.52	15	1.00	31	8.0	91.9	0.2	0.78	33	0.78
Norway	2.85	21	1.10	29	14.8	77.7	15.1	0.87	30	0.79
Poland	5.80	4	1.24	24	4.5	94.8	1.4	1.03	28	0.84
Slovak R.	4.65	9	2.19	7	22.3	75.0	5.5	2.04	7	0.93
Slovenia	3.33	16	1.93	11	33.7	65.1	2.5	1.77	11	0.92
Spain	2.71	23	1.22	25	20.3	81.2	-2.9	1.19	22	0.98
Sweden	4.95	7	1.59	16	10.3	89.5	0.5	1.51	16	0.95
Switzerland	1.30	34	1.12	27	74.6	24.9	1.0	1.04	27	0.92
Turkey	8.00	1	3.43	4	18.3	87.8	-12.2	3.02	5	0.88
UK	1.89	30	1.09	30	33.1	71.7	-9.6	0.99	29	0.91
USA	1.87	31	1.11	28	35.2	57.4	14.8	1.05	26	0.94

When volatility is measured using log deviations from HP filtered trend correlation between the measured volatility of the unadjusted quarterly GDP series and volatility of the seasonally adjusted series is 0.73, but it is 0.94 when volitility is measured using log deviations from the trend obtained using Hamilton filter. This correlation is lowest, 0.43, when volatility is measured using log differences. Table 4 shows these correlations, both for volatility of GDP and for volatility of private consumption. It also shows the correlations for the ranks (Spearman's coefficient of correlation).

Table 4

Correlation matrices, volatility of GDP

	Log deviations, HP filter			**Log deviations, Hamilton filter**			**Log differences**		
	unadj.	adj.	annual	unadj.	adj.	annual	unadj.	adj.	Annual
unadj.	1.00	0.73	0.72	1.00	0.94	0.92	1.00	0.43	0.55
adj.	0.73	1.00	0.99	0.94	1.00	1.00	0.43	1.00	0.84
annual	0.72	0.99	1.00	0.92	1.00	1.00	0.55	0.84	1.00

Correlation matrix, rank of volatility of GDP

	unadj.	adj.	annual	unadj.	adj.	annual	unadj.	adj.	Annual
unadj.	1.00	0.63	0.59	1.00	0.88	0.88	1.00	0.49	0.47
adj.	0.63	1.00	0.99	0.88	1.00	0.99	0.49	1.00	0.83
annual	0.59	0.99	1.00	0.88	0.99	1.00	0.47	0.83	1.00

Correlation matrix, volatility of private consumption

	Log deviations, HP filter			**Log deviations, Hamilton filter**			**Log differences**		
	unadj.	adj.	annual	unadj.	adj.	annual	unadj.	adj.	Annual
unadj.	1.00	0.87	0.86	1.00	0.98	0.98	1.00	0.66	0.57
adj.	0.87	1.00	1.00	0.98	1.00	0.99	0.66	1.00	0.91
annual	0.86	1.00	1.00	0.98	0.99	1.00	0.57	0.91	1.00

Correlation matrix, rank of volatility of private consumption

	unadj.	adj.	annual	unadj.	adj.	annual	unadj.	adj.	Annual
unadj.	1.00	0.76	0.76	1.00	0.93	0.94	1.00	0.52	0.41
adj.	0.76	1.00	0.99	0.93	1.00	0.98	0.52	1.00	0.85
annual	0.76	0.99	1.00	0.94	0.98	1.00	0.41	0.85	1.00

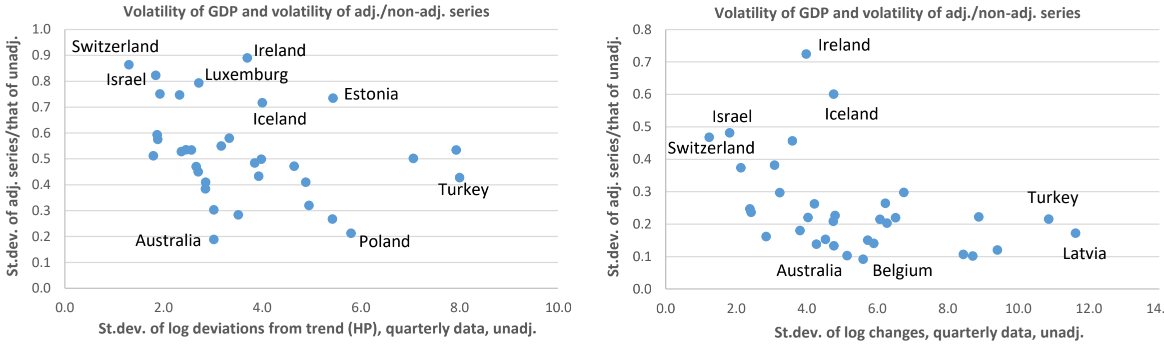
Table 4 shows that correlations are generally higher between volatility of annual series and volatility of seasonally adjusted series than between volatility of annual series and unadjusted series. When the HP filter is used, and also when Hamilton filter is used, this correlation is above 0.995, but when log differences are used this correlation is 0.84.

Table 3 shows that in terms of volaility of the unadjusted GDP series Turkey‘s economy is most volatile, but when we consider volatility of the seasonally adjusted series Turkey is in the fourth place. Iceland is in the 10th place when we consider volatility in the unadjusted series but in the 6th place in terms of volatility of seasonally adjusted series, and also in the 6th place in terms of volatility of the annual series. Australia is in the 19th place when we consider volatility of the unadjusted series for GDP but in the 34th place out of 34 when we consider volatility of the seasonally adjusted series and when we consider volatility of the annual series.

Columns 5-7 in Table 3 show the relative contributions of the terms on the right hand side in Equation (4) to the variance of log deviations of the unadjusted series. Column 5 and 6 show that the relative contributions of the adjusted series and the seasonal factors vary a lot. In the case of Australia, Belgium, New Zealand and Poland, the variance of the seasonal factors explains more than 90% of the variance in the log deviations of the unadjusted series, but in Ireland the variance in the seasonal factors explains only 18.7%, in Switzerland 24.9%, and in Iceland 45.9%.

Figure 2 shows scatterplots of the ratio of volatility of the seasonally adjusted series for GDP against volatility of the unadjusted series. The figure to the left shows outcomes when log deviations from trend obtained using the HP filter is used, while the figure to the rights shows outcomes when log changes are used.

Figure 2



The first two columns in Table 5 show the distribution of the relative contributions of the seasonally adjusted series for the case where volatility is measured using log deviations from HP trend (column 5 in Table 3).

Table 5

Contributions from the variance of the seasonally adjusted series

Log deviations, HP filter		**Log deviations, Hamilton filter**		**Log differences**	
Contribution	*Freq.*	*Contribution*	*Freq.*	*Contribution*	*Freq.*
0-5%	2	0-20%	1	0-1%	1
5-10%	3	20-40%	4	1-2%	7
10-20%	6	40-60%	6	2-5%	12
20-30%	11	60-70%	9	5-10%	7
30-40%	4	70-80%	5	10-20%	2
40-50%	0	80-90%	6	20-25%	3
>50%	8	>90%	3	>25%	2
Total	34	Total%	34	Total	34

When the method proposed by Hamilton is used to estimate the trend the contribution of the variance of the log deviations of the seasonally adjusted series is generally larger as shown in columns 3 and 4 in Table 5. But if log changes in the series are used to measure volatility the contributions of the seasonally adjusted series is generally smaller and the contributions of the seasonal factors larger as shown in columns 5 and 6 in Table 5. In this case where volatility is measured using log changes the contribution of the variance of the seasonally adjusted series in Ireland is largest, 52.4%, with Iceland in second place with 36.1%, and Israel in third place with 23.2%.

4. Volatility of seasonally adjusted quarterly data versus annual data

The last column in Table 3 shows volatility of annual data for GDP dvided by volatility of quarterly seasonally adjusted data. In the case shown in Table 3 where HP filter is used to calculate the trend this ratio is always below unity but usually close to unity. Table 6 shows the distribution of this ratio. In our sample of 34 countries we find that for 23 countries this ratio is above 0.90. The country where this ratio is lowest is Australia where it is 0.69. For Iceland the ratio is 0.83, well below 0.90.

Table 6
Distribution of relative volatility of GDP. Annual/quarterly

	No. of countries
0.98-1.00	2
0.96-0.98	3
0.94-0.96	6
0.92-0.94	8
0.90-0.92	4
0.75-0.90	10
0.60-0.75	1
Total	34

When log changes are used to measure volatility the ratio of volatility of annual and seasonally adjusted quarterly data for GDP in Iceland is 1.19, which is the lowest ratio in our data set. The second lowest ratio is in Norway where it is 1.28. The same measure gives the ratio of 2.47 for the relative voltility in private consumption in Iceland, which explains why volatility of annual data for consumption in Iceland exceeds volatility of annual GDP even though volatility of seasonally adjusted consumption is far less than the volatility of seasonally adjusted GDP.

We find that the ratio of annual to quarterly volatility of private consumption in Iceland ranks the 12th highest when log differences are used to measure volatility. This ratio is highest for US data where it is 3.38 making the volatility of annual data on consumption almost equal to the voltility in annual data on GDP, while quarterly seasonally adjusted data for private consumption in the US is much less volatile than GDP.

If log deviations from trend are used to measure volatility Equation (6) can be used to approximate the ratio of standard deviations of quarterly seasonally adjusted data and the standard deviation of the annual data.

$$\frac{St.dev[\hat{X}_y]}{St.dev[\hat{X}_q]} \approx \frac{1}{4}\left[4 + 2Corr\left(\hat{X}_q, \hat{X}_q(-3)\right) + 4Corr\left(\hat{X}_q, \hat{X}_q(-2)\right) + 6Corr\left(\hat{X}_q, \hat{X}_q(-1)\right)\right]^{1/2} \quad (6)$$

Where $\hat{X}_y$ is the log deviation of annual data from its trend and $\hat{X}_q$ is log deviation of quarterly data from its trend.

For log changes this approximate formula is valid for the quarterly series X_q and the corresponding annual series X_y:

$$\frac{St.dev[Dlog(X_y)]}{St.dev[Dlog(X_q)]} \approx \Bigg[\frac{11}{4} + 5 \cdot Corr\left(Dlog(X_q), Dlog\left(X_q(-1)\right)\right)$$

$$+\frac{31}{8} Corr\left(Dlog(X_q), Dlog\left(X_q(-2)\right)\right) + \frac{5}{2} Corr\left(Dlog(X_q), Dlog\left(X_q(-3)\right)\right)$$

$$+\frac{5}{4} Corr\left(Dlog(X_q), Dlog\left(X_q(-4)\right)\right) + \frac{1}{2} Corr\left(Dlog(X_q), Dlog\left(X_q(-5)\right)\right)$$

$$+\frac{1}{8} Corr\left(Dlog(X_q), Dlog\left(X_q(-6)\right)\right)\Bigg]^{1/2} \quad (7)$$

Both equations explain the ratio of annual to quarterly volatility in terms of autocorrelations. If we take the volatility of GDP and volatility of private consumption in Iceland measured by the standard deviations of the log changes then for the unadjusted series we have that volatility of GDP is 4.76% while volatility of private consumption is considerably higher, 6.81%. The ratio of the standard deviations is 1.43. As it happens the variance of the seasonal factors explains only 67.4% of the total variance in the unadjusted series for GDP and the standard deviations of log changes in the seasonally adjusted series is 2.86%. In the case of consumption the variance of the seasonal factors contributes 92.6% of the total variance in the unadjusted series and the standard deviations of log changes in the seasonally adjusted series is 2.17%, considerably smaller than the volatility of the seasonally adjusted series for GDP. The ratio of these standard deviations is only 0.76. When we consider the volatility of the annual data the standard deviation of log changes in GDP is again much smaller, 3.42%, while the standard deviation of the log changes in private consumption is 5.37%, and the ratio is 1.57. In terms of Equation (7) the reason for this is that autocorrelations in seasonally adjusted data for private consumption in Iceland are much higher than in seasonally adjusted data for GDP.

If we look at other measures of volatility we do not find these large changes in the relative volatility of consumption and GDP in Iceland as we find when we measure volatility using log changes. Instead we find private consumption persistently more volatile than GDP.

For the German economy we find unadjusted data for consumption to be more volatile than unadjusted data for GDP when log deviations from HP filter and when log changes are used to mesure volatility but for seasonally adjusted data and annual data consumption is less volatile than GDP. The same is true for Ireland. This is the other way around in the data for Poland where unadjusted data for consumption are much less volatile than GDP while seasonally adjusted data and annual data for consumption are much more volatile than GDP when log deviations from HP trend are used to measure volatility.

5. Volatility of private consumption versus volatility of GDP

When comparing volatility of private consumption and of GDP, Iceland is an outlier with very high ratio of volatility of private consumption compared to volatility of GDP. It is No. 2 for all three types of data when we use HP filter to estimate the trend, after Israel which is No. 1 when unadjusted data are used, South Korea which is No. 1 when seasonally adjusted data are used, and Australia which is No. 1 when annual data are used. Iceland is No. 1 for unadjusted and seasonally adjusted quarterly series when we use Hamilton filter to estimate the trend but in second place for annual data where Australia is No. 1. Iceland is in the fifth place in terms of the ratio of volatility of private consumption to volatility of GDP when log changes are used to measure volatility of unadjusted data, it is in the 27th place for seasonally adjusted data, but in the first place when annual data are used. When annual data are used and volatility measured using log deviations from trend private consumption is relatively most volatile in Australia, both when HP filter is used to estimate the trend and also when the Hamilton filter is used. When log deviations from trend obtained from HP filter are used the ratio is highest for Israel when unadjusted data are used but highest for South Korea when seasonally adjusted data are used.

Figure 3 below shows scattergrams for volatility of GDP and volatility of private consumption for the countries in our sample. In the figures on the left volatility is measured by standard deviation of log deviations from HP trend while in the figures on the right volatility is measure using log changes. The top row shows volatility of unadjusted data, the middle row volatility of seasonally adjusted data and the bottom row shows volatility of annual data. The orange line is the 45° line separating those countries where volatility of consumption is larger than volatility of GDP from those where volatility of consumption is smaller.

Figure 3

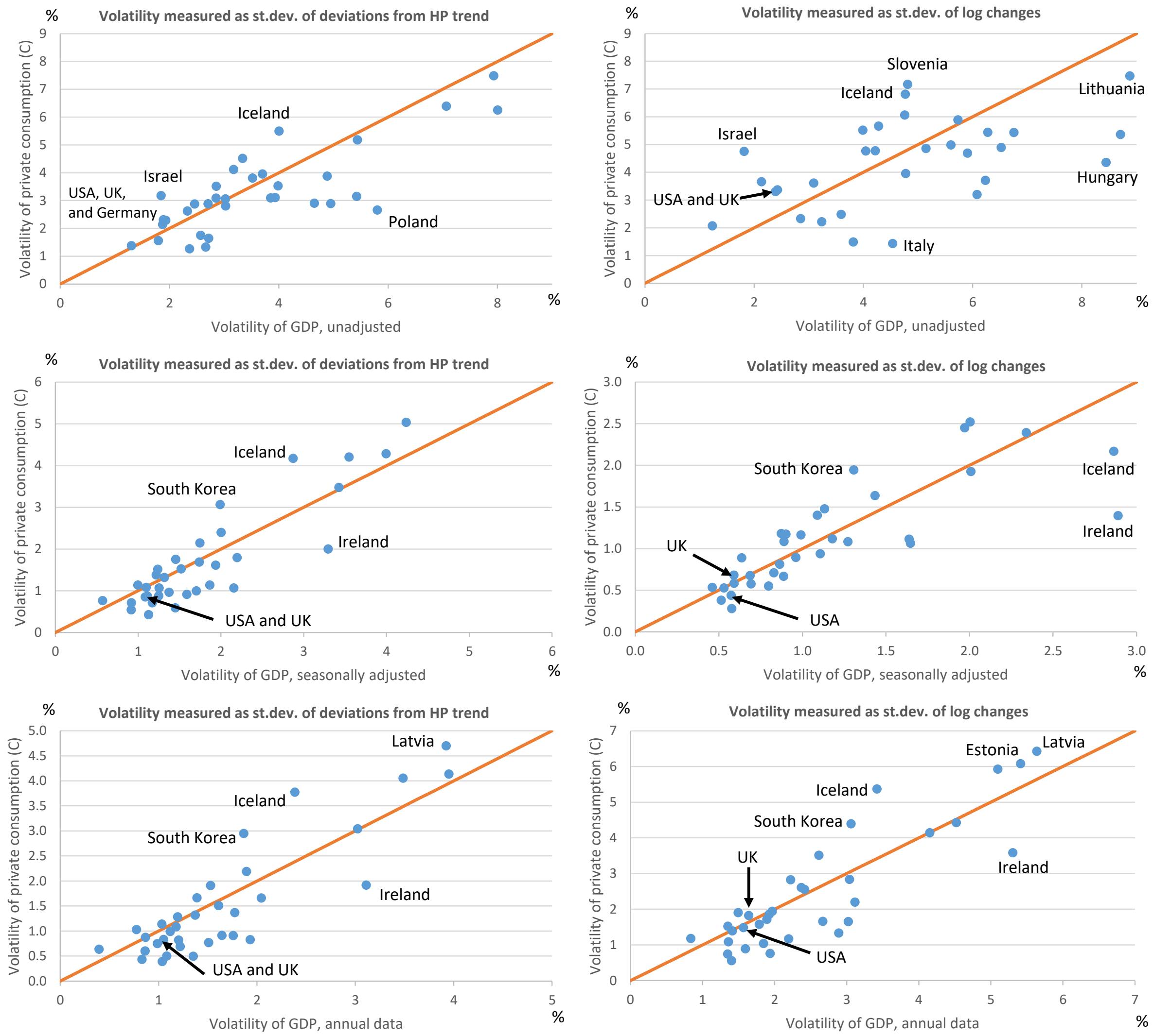


Table 7 shows the distribution of the ratios of volatility of private consumption to the volatility of GDP using different measures of volatilty and different types of data. The bottom row of the table shows the percentage of the 34 countries where volatility of consumption is smaller than volatility of GDP. For every method for measuring volatility, and all data types, consumption is less volatile than GDP in more than half of these economies. But it is only in the case of annual data and when log changes are used to measure volatility that the share of economies where consumption is less volatile than GDP is above 60%. In this case the share is 61.8%.

Table 7

Frequencies of relative volatility of C and GDP using different measures of volatility and types of data									
Measure:	**Log deviations from HP-trend**			**Log dev. from Hamilton trend**			**Log-changes**		
	Not adj.	Seas. adj.	Annual	Not adj.	Seas. adj.	Annual	Not adj.	Seas. adj.	Annual
<0.6	5	6	9	3	6	8	6	2	8
0.6-0.8	6	8	6	8	5	6	7	7	4
0.8-1	7	5	5	7	8	6	7	11	9
1-1.2	10	8	9	12	7	7	4	5	7
1.2-1.4	5	5	2	3	5	5	5	8	3
>1.4	1	2	3	1	3	2	5	1	3
Total	34	34	34	34	34	34	34	34	34
<1 (%)	52.9	55.9	58.8	52.9	55.9	58.8	58.8	58.8	61.8

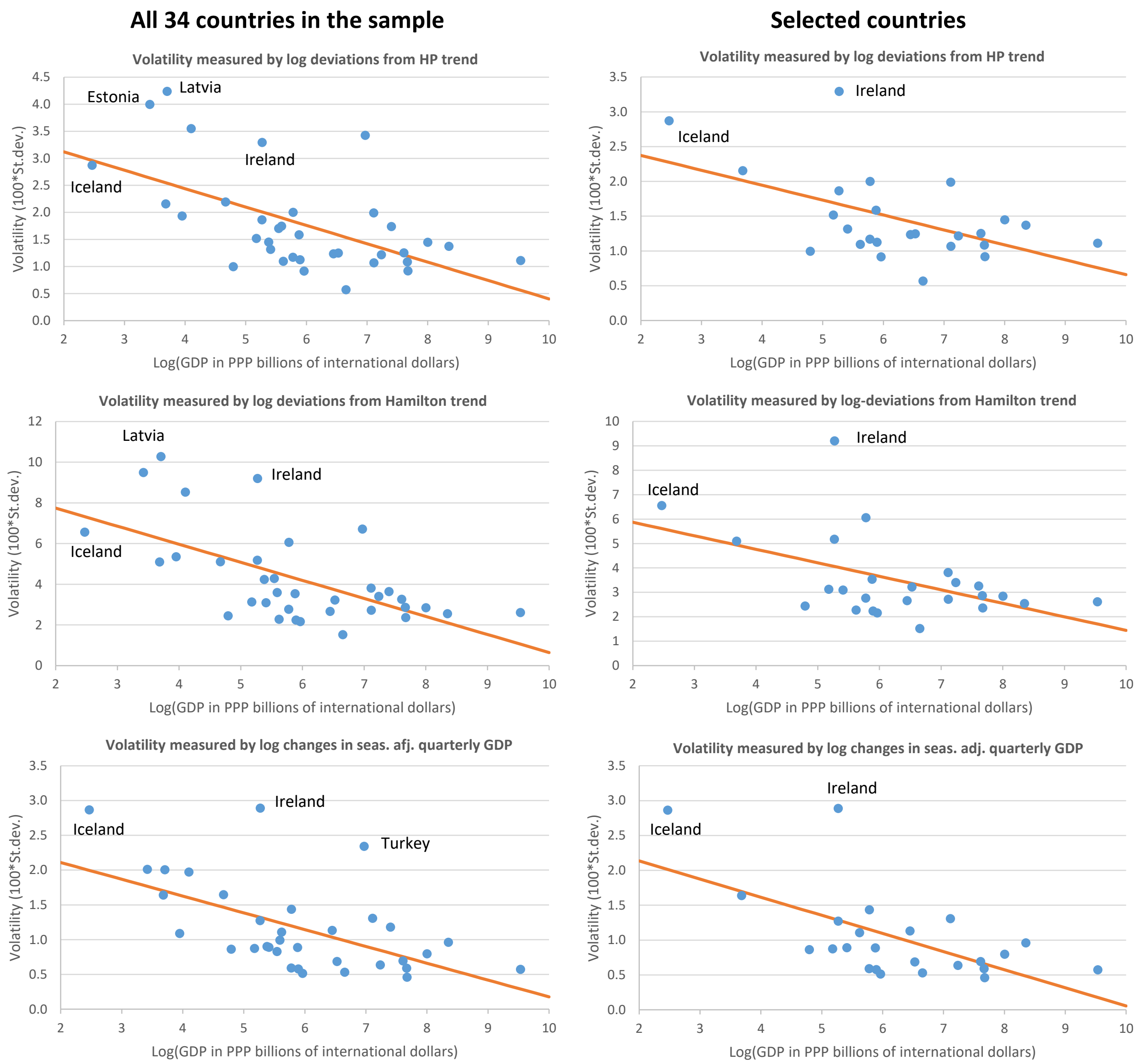
6. Volatility of GDP and the size of the economy

Fuceri and Karras (2007) and Alouini and Hubert (2010) study the relationship between volatility of GDP and the size of the economy. Both find that volatility declines with the size of the economy, which seems intuitive as larger economies tend to be less open and therefore less vulnerable to international shocks. Usually the production in large economies is more diversified which also should make them more resilient to shocks.

Figure 4 shows scatterplots of volatility against log of the size of the economy in terms of GDP in PPP billions of international dollars in 2006, a year which is roughly the middle of our time serles.[2] The first row shows the outcomes when volatility is measured by log deviations of the seasonally adjusted series from HP filtered trend, the second row shows outcomes when volatility is measured by log deviations from Hamilton filtered trend and the last row shows outcomes when volatility is measured by log changes in seasonally adjusted GDP. In the figures to the left all 34 countries are include, but in the figures to the right the following 10 countries have been left out because their economies are considered less comparable to the Icelandic economy. The countries that are excluded are the following former communist states and emerging markets countries: Chile, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Mexico, Slovak Republic, Slovenia and Turkey.

[2] The data are from IMF‘s website.

Figure 4 Volatility of seasonally adjusted GDP and size of the economy



The orange line in the figures is the estimated linear trend through the data points. In all cases the trend is significantly negative which confirms the main result in Fuceri and Karras (2007) and Alouini and Hubert (2010) for our data set. The point for Iceland is above the line in four cases, on the line in one case and slightly below the line in one case, the case where log deviations from trend otained from the Hamilton filter are used to measure volatility. This indicates that GDP in Iceland is probably more volatile than should be expected given the size of the economy.

Figure 4 also shows that our estimates of the relationship between volatility and the size of the economy indicate that volatility of GDP in the USA (the points farthest to the right in the figures) is very much larger than what should be expected given the size of the economy. This conclusion is independent of the method used to measure volatility.

7. Conclusions and discussion

In this paper we have discussed various aspects of volatility of GDP and private consumption for 34 OECD countries. We have focussed on Iceland and compared volatility of GDP and consumption in this country to the volatility of these variables in the other countries. We have found that in terms of volatility of both GDP and private consumption Iceland is among the most volatile in our sample. Iceland is also among those counties where seasonal factors contribute relatively small part of the total variance in the unadjusted series, with one exception, the case of the variance of log changes in private consumption, which explains why, in this case, data for seasonally adjusted consumption is less volatile than data for seasonally adjusted GDP in Iceland. Much higher autocorrelations in log changes in seasonally adjusted private consumption than in log changes in seasonally adjusted GDP explain why consumption is much more volatile than GDP when log changes of annual data are used to measure volatility. There are several other cases where the ratio of volatility of consumption to volatility of GDP is different depending on which method is used to measure volatility.

It seems natural to use seasonally adjusted data rather than unadjusted data when assessing volatility of economic variables and possible problems and costs associated with it. There are obvious seasonal variations in consumption which can be considered proper parts of rational households‘ efforts to optimize their utility. Some seasonal variations in production, e.g. in an economy like Iceland, where tourism and fisheries are important contributors is also part of proper operation of the economy and sometimes predictable. It seems natural to filter away "good", predictable variations to be able to focus on the "bad" volatility. It is less obvious that we should prefer measures of volatility based on seasonally adjusted quarterly data to measures based on annual data, but they can, as shown above, give a very different picture of volatility of economic data.

We have also estimated the relationship between volatility of GDP and logarithm of the size of the economy. As two previous studies of this issue, Fuceri and Karras (2007) and Alouini and Hubert (2010), we conclude that volatility declines with size of the economy . Using the estimated relationship between these variables we are able to conclude that volatility of GDP for Iceland is probably larger than what is to be expected when the small size of the economy is taken into account.

We have used three methods to measure volatility: standard deviation of log deviations from HP trend and from Hamilton trend and log changes in the series. For the countries in our sample the measurements of volatility obtained using these different methods are highly correlated but there are important exceptions. That is somewhat problematic because there is no agreement on which measure is best. For the volatility of consumption that problem is related to the problem of finding which utility function is best. If traditional utility functions are relevant for determining households‘ decisions measuring volatility of consumption by the standard deviation of log deviations from trend is probably best, but if some modern variant of utility functions, including the popular assumption of habit persistence assumed in many macro models, or some version of the prospect theory, volatility of consumption may be best measured by the standard deviation of log changes in consumption. The cost of the volatility of GDP must also be related to lower utility because of volatility of consumption and of labour opportunities.

Appendix A

Table A.1 is identical to Table 3 in the text except that here the Hamilton filter is used to estimate the trend rather than the HP filter.

Table A.1

	Standard deviation of log deviations of GDP from Hamilton trend									
	Quarterly data (%)				**Contribution to the variance of the unadj. series (%)**			**Annual data (%)**		Annual/ seas.adj. quarterly st.dev.
	Unadj. series	Rank	S. adj. series	Rank	S. adj. series	Seas. factors	2*Co-variance	St.dev	Rank	
Australia	3.29	28	1.52	34	20.5	78.6	0.9	1.06	34	0.70
Austria	3.77	23	2.77	25	52.5	46.7	0.8	2.38	28	0.86
Belgium	3.69	25	2.16	33	35.3	63.4	1.4	1.99	32	0.92
Chile	4.50	17	3.59	16	64.2	34.7	1.1	3.47	15	0.97
Czech R.	5.46	14	4.28	12	61.0	42.2	-3.2	4.21	12	0.98
Denmark	3.74	24	3.10	22	68.9	31.4	-0.4	2.98	20	0.96
Estonia	10.18	2	9.49	2	86.7	12.6	0.8	9.20	2	0.97
Finland	6.10	11	5.18	9	71.2	29.1	-0.3	4.83	10	0.93
France	2.82	33	2.36	30	69.5	29.9	0.6	2.11	31	0.89
Germany	3.04	31	2.85	24	86.5	16.5	-2.9	2.84	23	1.00
Greece	7.31	6	6.06	7	66.9	35.1	-2.0	5.54	7	0.91
Hungary	6.70	8	4.24	13	40.9	61.2	-2.1	4.19	13	0.99
Iceland	7.08	7	6.56	6	84.6	14.6	0.8	6.26	5	0.95
Ireland	9.43	5	9.20	3	95.4	2.9	1.7	9.15	3	0.99
Israel	3.32	27	3.12	21	88.7	8.4	2.9	3.10	19	0.99
Italy	3.91	21	3.26	19	69.2	35.4	-4.6	2.91	22	0.89
Japan	3.28	29	2.55	28	58.0	40.1	1.9	2.40	27	0.94
S. Korea	5.04	16	3.81	14	56.7	43.8	-0.5	3.54	14	0.93
Latvia	12.31	1	10.28	1	70.7	30.1	-0.8	9.85	1	0.96
Lithuania	9.99	3	8.53	4	69.8	34.4	-4.2	8.73	4	1.02
Luxemburg	5.36	15	5.10	11	90.6	9.4	0.0	4.70	11	0.92
Mexico	3.92	20	3.64	15	87.3	15.0	-2.3	3.17	18	0.87
Netherlands	3.82	22	3.22	20	71.3	27.6	1.1	2.92	21	0.91
New Zealand	4.18	19	2.44	29	33.8	64.9	1.3	2.42	26	0.99
Norway	3.62	26	2.28	31	40.3	49.5	10.2	1.97	33	0.86
Poland	6.55	10	2.66	26	17.6	79.9	2.5	2.48	25	0.93
Slovak R.	6.59	9	5.11	10	61.9	38.9	-0.8	5.18	8	1.02
Slovenia	5.84	13	5.35	8	82.8	21.2	-4.0	5.17	9	0.97
Spain	4.23	18	3.40	18	64.6	33.5	2.0	3.21	17	0.94
Sweden	5.88	12	3.54	17	35.6	62.9	1.5	3.46	16	0.98
Switzerland	2.32	34	2.24	32	92.8	7.9	-0.7	2.19	30	0.98
Turkey	9.95	4	6.71	5	44.7	56.4	-1.1	5.70	6	0.85
UK	3.26	30	2.87	23	76.3	24.0	-0.3	2.66	24	0.93
USA	2.92	32	2.61	27	77.2	23.1	-0.2	2.34	29	0.90

Table A.2 is identical to Table 3 in the text except that volatility is measured using log changes.

Table A.2

	Standard deviation of log changes in GDP									
					Contribution to the variance					Annual/
	Quarterly data (%)				**of the unadj. series (%)**			**Annual data (%)**		seas.adj.
	Unadj.		S. adj.		S. adj.	Seas.	2*Co-			quarterly
	series	Rank	series	Rank	series	factors	variance	St.dev	Rank	st.dev.
Australia	5.14	15	0.53	32	1.1	98.4	0.5	0.84	34	1.58
Austria	4.28	21	0.59	28	1.9	97.4	0.7	1.59	26	2.69
Belgium	5.60	14	0.51	33	0.8	99.0	0.2	1.35	33	2.62
Chile	4.76	19	0.99	16	4.3	93.4	2.3	2.22	17	2.24
Czech R.	5.90	12	0.83	23	2.0	96.0	2.0	2.67	13	3.22
Denmark	4.04	23	0.89	19	4.9	94.8	0.3	1.79	24	2.01
Estonia	6.75	7	2.01	4	8.8	91.2	-0.1	5.41	2	2.69
Finland	6.28	9	1.27	11	4.1	91.9	4.0	3.02	11	2.38
France	2.85	29	0.46	34	2.6	96.7	0.7	1.36	31	2.96
Germany	2.13	32	0.80	24	14.0	77.0	9.0	1.94	20	2.43
Greece	6.52	8	1.43	9	4.8	91.1	4.1	4.15	6	2.89
Hungary	8.44	6	0.90	18	1.1	96.0	2.8	2.61	14	2.90
Iceland	4.76	18	2.86	2	36.1	67.4	-3.5	3.42	7	1.19
Ireland	3.99	24	2.89	1	52.4	35.9	11.7	5.31	3	1.84
Israel	1.82	33	0.87	21	23.2	66.5	10.4	1.92	21	2.20
Italy	4.53	20	0.69	25	2.3	94.2	3.5	1.89	22	2.73
Japan	3.23	27	0.96	17	8.8	87.8	3.4	1.84	23	1.92
S. Korea	6.08	11	1.31	10	4.6	91.5	3.9	3.06	9	2.34
Latvia	11.62	1	2.00	5	3.0	94.0	3.1	5.64	1	2.81
Lithuania	8.88	4	1.97	6	4.9	89.7	5.4	5.10	4	2.59
Luxemburg	3.59	26	1.64	8	20.8	76.3	2.8	2.89	12	1.76
Mexico	3.09	28	1.18	12	14.6	83.4	2.0	2.42	15	2.05
Netherlands	3.81	25	0.69	26	3.2	95.2	1.5	1.97	19	2.87
New Zealand	5.73	13	0.86	22	2.3	97.3	0.5	1.35	32	1.56
Norway	4.22	22	1.11	14	6.9	86.1	7.0	1.41	29	1.28
Poland	9.41	3	1.13	13	1.4	98.9	-0.4	1.49	28	1.32
Slovak R.	6.23	10	1.65	7	7.0	89.2	3.9	3.04	10	1.85
Slovenia	4.81	16	1.09	15	5.1	89.6	5.2	3.11	8	2.86
Spain	4.77	17	0.64	27	1.8	98.4	-0.1	2.37	16	3.73
Sweden	8.71	5	0.89	20	1.0	98.9	0.1	2.20	18	2.47
Switzerland	1.23	34	0.58	30	21.9	71.6	6.6	1.40	30	2.43
Turkey	10.87	2	2.34	3	4.6	99.9	-4.5	4.52	5	1.93
UK	2.39	31	0.59	29	6.1	97.3	-3.4	1.64	25	2.78
USA	2.42	30	0.57	31	5.6	89.5	4.9	1.57	27	2.73

Appendix B

Let X_q be a quarterly series and X_q^{tr} its quarterly trend so that log deviations from trend is $log\left(X_q/X_q^{tr}\right)$. If deviations from trend are small numbers allowing the use of the approximation $log(1+x) \approx x$ the following approximation is valid when $\hat{X}_y = log\left(X_y/X_y^{tr}\right)$ is the log deviation of annual data from a trend:

$$Var\left[\hat{X}_y\right] = Var\left[log\left(\frac{X_q(-3)+X_q(-2)+X_q(-1)+X_q}{X_q^{tr}(-3)+X_q^{tr}(-2)+X_q^{tr}(-1)+X_q^{tr}}\right)\right]$$

$$\approx Var\left[\frac{X_q(-3)+X_q(-2)+X_q(-1)+X_q}{X_q^{tr}(-3)+X_q^{tr}(-2)+X_q^{tr}(-1)+X_q^{tr}} - 1\right]$$

$$= Var\left[\frac{X_q(-3)-X_q^{tr}(-3)+X_q(-2)-X_q^{tr}(-2)+X_q(-1)-X_q^{tr}(-1)+X_q-X_q^{tr}}{X_q^{tr}(-3)+X_q^{tr}(-2)+X_q^{tr}(-1)+X_q^{tr}}\right]$$

$$\approx Var\left[\frac{X_q^{tr}(-3)\hat{X}_q^{tr}(-3)+X_q^{tr}(-2)\hat{X}_q^{tr}(-2)+X_q^{tr}(-1)\hat{X}_q^{tr}(-1)+X_q^{tr}\hat{X}_q^{tr}}{X_q^{tr}(-3)+X_q^{tr}(-2)+X_q^{tr}(-1)+X_q^{tr}}\right]$$

$$\approx Var\left[\frac{\hat{X}_q^{tr}(-3)+\hat{X}_q^{tr}(-2)+\hat{X}_q^{tr}(-1)+\hat{X}_q^{tr}}{4}\right]$$

$$\approx \frac{1}{16}\left[Var\left(\hat{X}_q\right)+2Cov\left(\hat{X}_q,\hat{X}_q(-3)\right)+4Cov\left(\hat{X}_q,\hat{X}_q(-2)\right)+6Cov\left(\hat{X}_q,\hat{X}_q(-1)\right)\right]$$

wherefrom it follows that:

$$\frac{St.dev\left[\hat{X}_y\right]}{St.dev\left[\hat{X}_q\right]} \approx \frac{1}{4}\left[4+2Corr\left(\hat{X}_q,\hat{X}_q(-3)\right)+4Corr\left(\hat{X}_q,\hat{X}_q(-2)\right)+6Corr\left(\hat{X}_q,\hat{X}_q(-1)\right)\right]^{1/2}$$

In our sample of 34 countries we find for log deviations of GDP from trend obtained using HP filter that the largest absolute error when using this approximation is 13.0%. The average absolute error is 4.8%. If Hamilton filter is used to calculate the trend the largest absolute error is 29.3% and the average absolute error is 5.1%.

For the variance of the log change in the series, also assuming that the approximation $log(1+x) = x$ is valid, we have that:

$$Var\left(Dlog\left(X_y\right)\right) \approx Var\left(log\left(\frac{X_q+X_q(-1)+X_q(-2)+X_q(-3)}{X_q(-4)+X_q(-5)+X_q(-6)+X_q(-7)}\right)\right)$$

$$\approx Var\left(\frac{X_q+X_q(-1)+X_q(-2)+X_q(-3)}{X_q(-4)+X_q(-5)+X_q(-6)+X_q(-7)} - 1\right)$$

$$= Var\left(\frac{X_q+X_q(-1)+X_q(-2)+X_q(-3)-X_q(-4)-X_q(-5)-X_q(-6)-X_q(-7)}{X_q(-4)+X_q(-5)+X_q(-6)+X_q(-7)}\right)$$

The nominator gives that:

$$\left[X_q-X_q(-1)+X_q(-1)-X_q(-2)+X_q(-2)-X_q(-3)+X_q(-3)-X_q(-4)\right]$$

$$+\left[X_q(-1)-X_q(-2)+X_q(-2)-X_q(-3)+X_q(-3)-X_q(-4)+X_q(-4)-X_q(-5)\right]$$

$$+\left[X_q(-2) - X_q(-3) + X_q(-3) - X_q(-4) + X_q(-4) - X_q(-5) + X_q(-5) - X_q(-6)\right]$$
$$+\left[X_q(-3) - X_q(-4) + X_q(-4) - X_q(-5) + X_q(-5) - X_q(-6) + X_q(-6) - X_q(-7)\right]$$
$$= \left(X_q - X_q(-1)\right) + 2\left(X_q(-1) - X_q(-2)\right) + 3\left(X_q(-2) - X_q(-3)\right) + 4\left(X_q(-3) - X_q(-4)\right)$$
$$3\left(X_q(-4) - X_q(-5)\right) + 2\left(X_q(-5) - X_q(-6)\right) + \left(X_q(-6) - X_q(-7)\right)$$
$$\begin{aligned}\approx X_q(-1)Dlog(X_q) &+ 2X_q(-2)Dlog\left(X_q(-1)\right) + 3X_q(-3)Dlog\left(X_q(-2)\right)\\ &+ 4X_q(-4)Dlog\left(X_q(-3)\right) + 3X_q(-5)Dlog\left(X_q(-4)\right) + 2X_q(-6)Dlog\left(X_q(-5)\right)\\ &+ X_q(-7)Dlog\left(X_q(-6)\right)\end{aligned}$$

Dividing through with the denominator $X_q(-4) + X_q(-5) + X_q(-6) + X_q(-7)$ and approximating the ratios $X_q(-i)/\left[X_q(-4) + X_q(-5) + X_q(-6) + X_q(-7)\right], i = 1,2,\dots,7$ by $1/4$ and then calculate the variance and setting $Var\left(Dlog(X_q)\right) = Var\left(Dlog\left(X_q(-1)\right)\right)$= …= $Var\left(Dlog\left(X_q(-6)\right)\right)$ and $Corr\left(Dlog(X_q), Dlog\left(X_q(-1)\right)\right)$ = $Corr\left(Dlog\left(X_q(-1)\right), Dlog\left(X_q(-2)\right)\right)$ etc. gives that:

$$\begin{gathered}Var\left(Dlog(X_y)\right) \approx \frac{11}{4} + 5 \cdot Cov\left(Dlog(X_q), Dlog\left(X_q(-1)\right)\right) +\\ \frac{31}{8}Cov\left(Dlog(X_q), Dlog\left(X_q(-2)\right)\right) + \frac{5}{2}Cov\left(Dlog(X_q), Dlog\left(X_q(-3)\right)\right)\\ +\frac{5}{4}Cov\left(Dlog(X_q), Dlog\left(X_q(-4)\right)\right) + \frac{1}{2}Cov\left(Dlog(X_q), Dlog\left(X_q(-5)\right)\right)\\ +\frac{1}{8}Cov\left(Dlog(X_q), Dlog\left(X_q(-6)\right)\right)\end{gathered}$$

wherefrom it follows that:

$$\begin{gathered}\frac{St.dev\left[Dlog(X_y)\right]}{St.dev\left[Dlog(X_q)\right]} \approx \left[\frac{11}{4} + 5 \cdot Corr\left(Dlog(X_q), Dlog\left(X_q(-1)\right)\right)\right.\\ +\frac{31}{8}Corr\left(Dlog(X_q), Dlog\left(X_q(-2)\right)\right) + \frac{5}{2}Corr\left(Dlog(X_q), Dlog\left(X_q(-3)\right)\right)\\ +\frac{5}{4}Corr\left(Dlog(X_q), Dlog\left(X_q(-4)\right)\right) + \frac{1}{2}Corr\left(Dlog(X_q), Dlog\left(X_q(-5)\right)\right)\\ \left.+\frac{1}{8}Corr\left(Dlog(X_q), Dlog\left(X_q(-6)\right)\right)\right]^{1/2}\end{gathered}$$

In our sample of 34 countries we find for log changes of GDP that the largest absolute error from using this approximation is 11.5%. The average absolute error is 3.7%.

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