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Adaptation and loss aversion in the relationship between GDP and subjective well-being

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Abstract

We examine the roles of adaptation and loss aversion in the relationship between national income and subjective well-being. Earlier studies have found that people and nations tend to adapt to changes in income, and that well-being is more sensitive to income losses than to income gains. We apply models that allow for both adaptation and asymmetries to cross-country panel data. We find evidence for both short-run and long-run loss aversion. Asymmetry becomes more important over time because the effects of income increases become statistically insignificant, whereas the effects of income decreases are significant and large also in the long run.

Keywords: Subjective well-being, Life satisfaction, Happiness, Adaptation, Loss aversion, Output, Income, GDP, Economic growth, Macroeconomics, Easterlin paradox
JEL codes: O11, I31

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I. Introduction

Two well-established behavioural phenomena, hedonic adaptation and loss aversion, have the potential to affect the relationship between national income, or gross domestic product (GDP), and subjective well-being (SWB). Hedonic adaptation would lead the impacts of GDP changes to wear off in time, completely or partially. Loss aversion, to the extent that it is actually experienced instead of merely anticipated, would be reflected as larger well-being responses to negative GDP changes than to positive GDP changes.[1] To our knowledge, the only studies examining adaptation to GDP are Di Tella, MacCulloch, and Oswald (2003) and Di Tella and MacCulloch (2008). Both use repeated annual cross-sections from the Eurobarometer survey, which cover European countries over a number of years. The latter study also uses a single Gallup World Poll cross-section of individuals in a larger group of countries. Asymmetries in how well-being is affected by changes in GDP are examined by De Neve et al. (forthcoming) using three different international repeated cross-section surveys, including Eurobarometer. These papers present evidence for adaptation and asymmetries.

A second set of studies examines adaptation and loss aversion using micro-level panel data on incomes and subjective well-being. Di Tella, Haisken-DeNew, and MacCulloch (2010) and Vendrik (2013) study adaptation to income using data from the German Socio-economic Panel (GSOEP). Clark, D'Ambrosio, and Ghislandi (2016), also using the German panel, study adaptation to poverty and also extend their analysis to adaptation to any income drop. Di Tella, Haisken-DeNew, and MacCulloch (2010), D'Ambrosio and Frick (2012), and Boyce et al. (2013) all study loss aversion using the German panel. Boyce et al. (2013) also use the British Household Panel Survey (BHPS). Finally, Frijters, Johnston, and Shields (2011) use the Household, Income and Labour Dynamics in Australia (HILDA) survey and provide results on loss aversion. Similarly to the studies looking at the effects of national income, these studies find evidence for adaptation and loss aversion. The only exception is Clark, D'Ambrosio, and Ghislandi's (2016) study, which does not find evidence for adaptation to poverty or to any negative income change.

Despite the observed importance of adaptation and loss aversion, there are no studies which allow for both of these in the same model.[2] The lack of such studies has two consequences. First, it is clear that assuming away one of the phenomena may bias the results on the other. Therefore, we do not know how robust the findings on adaptation are to controlling for loss aversion and vice versa. Second, nothing is known about whether the asymmetries remain similar over time or whether adaptation to positive and/or negative changes leads to changes in the asymmetries. It has been hypothesised that adaptation to the effects of negative income changes may be different from adaptation to the effects of positive changes and some authors have called for research on the issue (e.g., Easterlin, 2009; De Neve et al., forthcoming). Furthermore, Clark, D'Ambrosio, and Ghislandi (2016) point out that income decreases that lead to poverty are a small minority of all income changes and, therefore, any results on adaptation to income changes on average may be driven by the positive changes and not be informative

[1]Kahneman and Tversky's (1979) original notion of loss aversion was related to decision making, but the authors note in their later study (Tversky & Kahneman, 1991) that knowledge of to what extent, and for how long, loss aversion is actually experienced would provide a criterion for evaluation of rationality of the loss aversion observed in decision making.

[2]Frijters, Johnston, and Shields (2011), using Australian survey data, go some way towards doing this by regressing life satisfaction on multiple lags of both positive and negative financial changes. The change variables are indicators of reporting a major financial improvement or a major financial worsening in the near past.

about adaptation to poverty. Similarly, it is not known whether the earlier results on adaptation also apply to negative national income changes because they are a minority of all changes. In this paper, we adopt an empirical model, novel in the subjective well-being literature, which incorporates both adaptation and loss aversion. We can, thus, avoid biases arising from ignoring one of the phenomena and provide first findings on how effect asymmetry changes over time.

Earlier studies have used either distributed lag (DL) or autoregressive distributed lag (ARDL) models to allow for adaptation to a continuous income variable. To model asymmetries, studies have regressed subjective well-being on positive and negative income changes. We combine these two approaches by using nonlinear autoregressive distributed lag (NARDL) models. Our subjective well-being data come from Eurobarometer surveys. The data cover more than 30 countries and include annual observations on many of the countries over three or four decades. Thus, the data cover multiple recessions and recoveries, which is ideal from the point of view of estimating asymmetries both in the short run and in the long run.[3]

Our results are consistent with earlier findings on the relationship between income (national or personal/household) and subjective well-being. Furthermore, the results are also consistent with the more general findings on how positive and negative economic changes are adapted to. The well-being changes associated with negative changes in national income are greater than those associated with positive changes. This asymmetry is observed both in the short run and in the long run, and it becomes more important over time. This stems from complete adaptation to positive changes and non-existent or, at best, far from complete adaptation to negative changes in national income.

The remainder of the paper is organised as follows. Section II reviews the earlier empirical models that have been used to study adaptation and loss aversion and lays out our empirical approach. Section III describes the data and presents the results. Section IV discusses our results and examines their robustness. Section V concludes.

II. Empirical Framework

A. Adaptation

In the subjective well-being (SWB) literature, adaptation to changes in circumstances is usually studied by examining the short- and long-run well-being effects of these changes. In the studies of adaptation, it is considered a sign of complete adaptation if a permanent change in circumstances affects SWB in the short run but has a long-run effect of zero. In the case of less-than-complete adaptation, the short-run effect is larger than the long-run effect but the long-run effect is greater than zero.

Previous studies have examined adaptation to changes in circumstances measured by indicator variables or adaptation to changes in continuous variables, such as income. For a review of studies of the former type, see Clark et al. (2008). Our focus is on the modelling techniques similar to those used in the latter group of studies. Adaptation to changes in a continuous income variable at the micro level and at the macro level is often modelled with a finite distributed lag model (Di Tella, Haisken-De New, & MacCulloch, 2010; Di Tella, MacCulloch, & Oswald,

[3] At the outset, a clear distinction between *short-run and long-run effects* (as in standard time series models) and *effects of short-run income fluctuations and long-run income changes* should be made. We focus on the former, as do the studies of adaptation listed above. However, we also take into account the possibly different effects of shorter-run fluctuations (such as business cycles) and long-run trend growth, as some studies mentioned below do.

2003; Di Tella & MacCulloch, 2008). Vendrik (2013) points out, however, that the model of adaptation can be improved in two ways by estimating ARDL models. First, ARDL models control for the effects of higher-order lags of income than the number of income lags included in the model. Second, ARDL models are able to control for adaptation to factors other than those included in the model. Applying an ARDL model, though estimated in the error correction form, to GSOEP data, Vendrik (2013) cannot reject the hypothesis of complete adaptation to income changes over the long run even though he finds significant well-being effects from income changes in the short run.

It should be noticed that there is a difference between adaptation at the micro level and adaptation at the macro level. In the individual-level studies of adaptation, it is important to take into account the different adaptation processes to changes in an individual's own income and to changes in the income of the individual's social reference group (Vendrik, 2013). When the analysis is conducted at the macro level, the estimate for the effect of the income variable measures the combined effect of the individual's income and the average income level in the country. However, the different timing of the two effects at the individual level may influence the estimates of adaptation at the macro level. For example, if the income of all individuals in a country increases by the same amount, the resulting change in social reference income could affect individual SWB later than the resulting change in an individual's own income. This would show up as slow adaptation to a change in average income at the macro level. Although we are not able to analyse the two micro-level effects separately, both are taken into account in our macro-level estimates. Thus, we are able to provide unbiased estimates of the short- and long-run effect of aggregate output on aggregate life satisfaction.

B. Loss Aversion

Loss aversion in the context of experienced well-being effects means that the well-being effect of a positive change (gain) is smaller than the effect of a negative change (loss) of the same size. The few papers regressing SWB on national, personal or household income that examine loss aversion do so by including positive and negative income changes as separate regressors (Di Tella, Haisken-De New, & MacCulloch, 2010; D'Ambrosio & Frick, 2012; Boyce et al., 2013; De Neve et al., forthcoming). All the studies find that negative changes have larger impacts than positive changes. As De Neve et al. (forthcoming) point out, results from such analyses are informative about the short run.[4] To our knowledge, nothing is known about long-run asymmetries.

The long-run asymmetry does not need to be similar to the short-run asymmetry. It is clear that long-run asymmetry is determined by the short-run asymmetry and adaptation, which may be different for positive and negative income changes. Indeed, although the aforementioned studies find evidence for complete adaptation to income changes on average, results obtained in some recent micro studies suggest that people do not adapt to negative economic changes such as income decreases (Clark, D'Ambrosio, & Ghislandi, 2016). Because asymmetry may be different in the long run than in the short run, regressing SWB on positive and negative income changes might not give an accurate description of what happens in the long run. For

[4]By "informative about the short run," we can mean either that income changes measure short-run fluctuations, in which case information on the effects of such fluctuations is obtained, or that the coefficients of the income change variables capture the short-run effects of the income changes (as in certain representations of DL and ARDL models, such as ours). The distinction between the two cases is the distinction made in footnote 3.

this reason, and also because not allowing for long-run asymmetry may bias the short-run results, it is important to study asymmetries using a more flexible empirical framework.

As mentioned earlier, short-run and long-run effects can, in general, be estimated by either DL or ARDL models. Our models which allow for both short-run and long-run asymmetry are ARDL models which make a distinction between positive and negative national income changes not only in the short run, but also in the long run. To our knowledge, using a nonlinear autoregressive distributed lag model is the only possible approach to estimate asymmetric effects of a continuous variable in the short run and in the long run.[5] Next, we will present a simple variant of such a model.

C. Empirical Model and Estimation Strategy

Our empirical model which allows for adaptation and loss aversion is

$$s_{i,t} = (1-\alpha)s_{i,t-1} + \beta\Delta y_{i,t} + \beta^{-}\Delta y_{i,t}D_{i,t} + \gamma y_{i,t-1} + \gamma^{-} y^{-}_{i,t-1} + \lambda_i + \eta_t + \epsilon_{i,t}, \qquad (1)$$

where $s_{i,t}$ is the average life satisfaction and $y_{i,t}$ is the log of real GDP per capita in country i in year t. $D_{i,t}$ is a dummy variable equal to 1 if country i experienced negative growth in y in year t. The partial sum $y^{-}_{i,t-1} = \sum_{\tau=I_i}^{t-1} \Delta y_{i,\tau}D_{i,\tau}$ is the sum of negative changes in y from the first year of the sample (I_i for country i) until year $t-1$. Equation (1) is the autoregressive distributed lag representation of the nonlinear ARDL model originally introduced by Schorderet (2001, 2003) and later discussed at length by Shin, Yu, and Greenwood-Nimmo (2014).[6] For now, the lag length is set to 1 in this baseline specification; we will allow for longer lags later. Country fixed effects λ_i and year fixed effects η_t are included in all specifications. Therefore, the estimated parameters are identified from the differences in time variation between countries.

We are interested in estimates of α, the speed of adjustment; β, the short-run effect of a positive change in y; $\beta + \beta^{-}$, the short-run effect of a negative change in y; $\frac{\gamma}{\alpha}$, the long-run effect of a positive change in y; and $\frac{\gamma+\gamma^{-}}{\alpha}$, the long-run effect of a negative change in y. Estimates of β^{-} and γ^{-} are measures of asymmetries in the short run and in the long run, respectively. From the perspective of our adaptation and loss aversion framework, α is the speed of adaptation. β and $\beta + \beta^{-}$ are the short-run effects as estimated in the earlier studies of loss aversion mentioned in the previous section. $\frac{\gamma}{\alpha}$ and $\frac{\gamma+\gamma^{-}}{\alpha}$ represent what is left of the short-run effects in the long run.

It has been argued by Richard Easterlin (e.g., Easterlin, 2013) that the GDP-SWB relationship is driven by a relationship between short-run fluctuations of GDP around its trend and SWB, whereas trend growth differences between countries are not associated SWB growth dif-

[5]Recent studies using the NARDL approach include Greenwood-Nimmo and Shin (2013) and Eberhardt and Presbitero (2015).

[6]The formulation of the nonlinear ARDL model by Schorderet (2001, 2003) and Shin, Yu, and Greenwood-Nimmo (2014) includes positive and negative changes of y ($\Delta y_{i,t}(1-D_{i,t})$ and $\Delta y_{i,t}D_{i,t}$) and positive and negative partial sums ($\sum_{\tau=I_i}^{t-1} \Delta y_{i\tau}(1-D_{i\tau})$ and $\sum_{\tau=I_i}^{t-1} \Delta y_{i\tau}D_{i\tau}$). Noticing that $y_{i,t-1}$ is the sum of a country-specific constant and the sum of all changes in y from the beginning of the sample until year $t-1$, it is easy to see that the two models are equivalent.

ferences.[7] To allow for the possiblity that trend growth and fluctuations around the trend have different effects on SWB, we also estimate our models controlling for the country-specific linear trend component of the output variable (T_i).[8] For more information about controlling for the trend component and the associated interpretations, see the appendix.

It is known that estimating a fixed effects model with a lagged dependent variable using ordinary least squares may yield biased results (Nickell, 1981). Therefore, in regressions in which we include the lagged dependent variable, we use the bias-corrected least squares dummy variables (LSDVC) method. The method was first developed by Kiviet (1995), and later recommended by Judson and Owen (1999) based on their Monte Carlo results. We use the bias approximations for unbalanced panels derived by Bruno (2005).

III. Data and Analysis

A. Data

Estimating model (1) requires annual country-level data on subjective well-being. The Eurobarometer survey is the only international survey which includes a subjective well-being question and has has been conducted annually over several decades, thus covering multiple recessions and recoveries for many countries. We have repeated cross-sections of individuals residing in 34 different European countries. We calculate annual country-level population-weighted averages of individuals' life satisfaction on a scale from 1 to 4 using the repeated cross-sections. Only surveys conducted in all member countries of the survey year were included in order to improve international comparability. Years covered vary by country. The longest time series start in 1975, and all series end in 2015. The real GDP per capita data up to and including 2014 are taken from the Penn World Tables. We extend the Penn World Tables data through 2020 using growth rates calculated from the IMF World Economic Outlook (April 2017) data and forecasts. Only actual GDP data are used in estimating the life satisfaction models and, thus, IMF estimations and projections are used only for the GDP trend extractions. We end up with 674 country-year averages of life satisfaction which will be regressed on the explanatory variables. Table 1 reports some descriptive statistics of these observations. Our data confirm the generally known feature of SWB, that is, that variation tends to be larger between countries than within countries over time. However, the within standard deviation is almost one-third of the overall standard deviation in our data. Due to inclusion of country fixed effects in all models, it is the within variation from which the parameter estimates are identified. Because we estimate asymmetries around zero economic growth, it is useful that more than one-sixth of the real GDP per capita changes are negative.

[7]For a recent analysis of these issues using Eurobarometer and World Values Survey, see Hovi and Laamanen (2016).

[8]A trend estimation period longer than our SWB data was chosen to alleviate the impact of post-2007 years on the trend estimates. Specifically, we include five years prior to the beginning of the SWB data and five years after its end. This results in the trend being estimated for 1970-2020 for most countries. For some countries, though, the output data begins after 1970, so the trend estimation period for these countries is shorter.

Table 1. Descriptive Statistics

Variable	N	Mean	SD	SD (within)	Min	Max
Life satisfaction (s)	674	2.99	0.34	0.10	2.02	3.71
GDP per capita in 2005 euros	674	23735	7910	5069	8632	52498
Economic growth (Δy)	674	0.019	0.032	0.031	-0.156	0.226
conditional on being negative ($\Delta y\| < 0$)	119	-0.028	0.030	0.023	-0.156	-0.001
Trend growth (ΔT)	674	0.021	0.008		0.010	0.041

Economic growth rates measured as log changes. Trend growth estimates based on linear time trends fitted to the log of real GPD per capita series from 1970 (or from the beginning of the Penn World Tables series if later than 1970) to 2020. The 674 country-years are: BEL, DNK, FRA, GBR, IRL, ITA, LUX, NLD in 1976-2015; GRC in 1982-2015; ESP, PRT in 1986-2015; DEU in 1991-2015; NOR in 1991-1995; AUT in 1996-2015; FIN, SWE in 1996-2014; BGR, CYP, CZE, EST, HRV, HUN, LTU, LVA, MLT, POL, ROU, SVK, SVN, TUR in 2005-2015; MKD in 2008-2015; ISL in 2011-2014; MNE in 2012-2015; SRB in 2013-2014.

B. Results from Simpler Models

We start by estimating simpler models that are obtained by imposing restrictions on the parameters of model (1). This facilitates comparisons to some earlier results and comparisons of the effects of imposing different restrictions. We begin with the simplest possible model with neither adaptation nor asymmetries. We then estimate a model allowing for adaptation but not loss aversion. Next, we estimate a model with asymmetries but no adaptation. Finally, we estimate equation (1) without any restrictions on the parameters.

Table 2 presents the results. The upper panel of the table shows the estimated coefficients on the explanatory variables, and the lower panel presents the effect estimates and tests of various relevant hypotheses. The first column reports results from a simple regression with the log of real GDP per capita as the only regressor (and controlling for country fixed effects and year effects). This model is obtained by assuming no differences between the short-run effects and the long-run effects ($\alpha = 1$, $\beta = \gamma$ and $\beta^- = \gamma^-$), implying no adaptation, and assuming no asymmetries ($\beta^- = \gamma^- = 0$). The coefficient estimate on the output variable is positive and statistically different from zero at the 10% level. Stevenson and Wolfers (2008) report a similar result using Eurobarometer data and employing the same specification. The second column adds the trend component of output. The coefficient of the output variable becomes larger and statistically significant at the 1% level. The test in the lower panel of the table suggests that the null of no association between the trend component and SWB cannot be rejected. Specifically, the null is that the coefficient of the trend component of output equals the negative of the coefficient of the output variable. This finding is in line with the earlier studies mentioned above.

Columns 3 and 4 of table 2 allow for adaptation but, by setting $\beta^- = \gamma^- = 0$, assume no asymmetries. The models are thus conventional ARDL models similar to the ones estimated by Vendrik (2013) using German micro data. The estimated speed of adjustment, α, is below 0.2

and significantly different from both 0 and 1.[9] The short-run coefficient, that is, the immediate effect (the first-year effect or the impact effect) of the output variable, is about 0.65 and statistically significant at the 1% level in both columns 3 and 4. The long-run coefficient, however, is much smaller and not statistically significant, regardless of whether or not the trend component is controlled for. The statistical significance in the short run and insignificance in the long run is in line with the results on the effects of national income presented by Di Tella and MacCulloch (2008) and the results on the effects of household income by Di Tella, Haisken-DeNew, and MacCulloch (2010) and Vendrik (2013).[10] Clark, D'Ambrosio, and Ghislandi (2016) argue that the results on adaptation to all income changes are not informative about adaptation to poverty because the income drops associated with poverty entry are a small minority of all income changes. Correspondingly, negative national income changes are a minority of all national income changes. As we will see, the above result of complete adaptation to national income changes masks a significant difference between adaptation to positive and negative changes.

Columns 5 and 6 present estimates from models that allow for asymmetries but not adaptation to the effects of output changes. The no-adaptation restriction means imposing $\alpha = 1$, $\beta = \gamma$ and $\beta^- = \gamma^-$. The variables of the models are the output variable and the partial sum variable which includes the past negative changes in the output variable and the current change if it is negative. The results point to statistically significant aversion to losses. The degree of loss aversion is much smaller when the trend component of output is included, partly reflecting the resulting larger coefficient on the output variable. Again, we cannot reject the hypothesis that trend growth's long-run effect on SWB is zero.

The results so far point to the importance of both adaptation and asymmetries. We now proceed to estimating equation (1), which allows for both of the two phenomena. The results are presented in columns 7 and 8 of table 2. The short-run effects of positive and negative changes in output are estimated to be almost 0.4 and about 1.4, respectively. The difference between the two parameters is statistically significant, indicating that there is significant loss aversion in the short run. The asymmetry is much more pronounced in the long run. This is because the long-run coefficient estimate on positive output changes is close to zero and the coefficient estimate on negative output changes is a bit larger than the corresponding short-run estimate. What is left from the effects of positive changes in the long run is not statistically significantly different from zero. In turn, negative changes are significantly associated with life satisfaction in the long run. Adjustment is somewhat faster compared to the models with adaptation only. As before, we cannot reject the hypothesis that trend growth does not have any effect on SWB in the long run. However, this result is not relevant because the long run effects of any positive changes are not statistically significantly different from zero. Because of this, we will discuss the findings in column 7.

Let us now turn to interpretation of the results. Clearly, the interesting questions concern the short-run and long-run SWB effects of positive and negative output changes. Furthermore, we are interested in the speed of adaptation, or, more generally, adjustment. Some care has to be taken in drawing conclusions about the short-run effects of output changes because the explanatory variable Δy is the sum of the change in the log of the real GDP's cycle component

[9] Also an earlier study by Blanchflower (2007) finds that the coefficient of the lagged dependent variable is large, and thus, adaptation is slow, in macro data compared to what has been found in studies using micro data.

[10] Di Tella, MacCulloch, and Oswald (2003) find evidence for adaptation but conjecture that adaptation is not complete. Their Eurobarometer data is relatively short (1975-1992) and they encourage future research to revisit the issue of adaptation.

Table 2. Models of Life Satisfaction.

			Adaptation		Asymmetry		Both	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
s_{t-1}			0.81***	0.81***			0.76***	0.76***
			(0.03)	(0.03)			(0.03)	(0.03)
y_t	0.33**	0.79***			0.22**	0.49**		
	(0.16)	(0.16)			(0.09)	(0.22)		
y_t^-					1.47***	1.25**		
					(0.37)	(0.56)		
Δy_t			0.66***	0.67***			0.38**	0.36**
			(0.13)	(0.13)			(0.15)	(0.16)
Δy_t^-							1.06***	1.07***
							(0.31)	(0.31)
y_{t-1}			0.03	0.05			0.04	0.01
			(0.03)	(0.06)			(0.03)	(0.07)
y_{t-1}^-							0.32***	0.33***
							(0.09)	(0.10)
T_t		-0.72***				-0.39		
		(0.24)				(0.29)		
T_{t-1}				-0.03				0.03
				(0.08)				(0.08)
α			0.19***	0.19***			0.24***	0.24***
			(0.03)	(0.03)			(0.03)	(0.03)
1st-year effect of Δy	0.33**	0.79***	0.66***	0.67***	0.22**	0.49**	0.38**	0.36**
	(0.16)	(0.16)	(0.13)	(0.13)	(0.09)	(0.22)	(0.15)	(0.16)
Long-run effect of Δy	0.33**	0.79***	0.18	0.28	0.22**	0.49**	0.14	0.06
	(0.16)	(0.16)	(0.17)	(0.31)	(0.09)	(0.22)	(0.13)	(0.28)
1st-year effect of Δy^-					1.69***	1.74***	1.43***	1.42***
					(0.35)	(0.43)	(0.25)	(0.25)
Long-run effect of Δy^-					1.69***	1.74***	1.45***	1.44***
					(0.35)	(0.43)	(0.36)	(0.37)
Long-run effect of ΔT		0.07		0.03		0.10		0.04
		(0.18)		(0.04)		(0.11)		(0.04)

OLS (cols 1, 2, 5 and 6) and bias-corrected (cols 3, 4, 7 and 8) estimates. N = 674. Country and year fixed effects included in all regressions. Upper panel presents the coefficient estimates and lower panel presents the estimated effects and hypothesis testing. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. Standard errors in parentheses are clustered at the country level (OLS models) or bootstrapped with 200 replications (bias-corrected models).

(ΔC) and the change in its trend component (ΔT). Because ΔT is, in the case of a linear trend, a country-specific constant, its effect is absorbed by the country fixed effect. Thus, the estimate of the short run effect of a positive change in output is an estimate of the effect of a change in the cycle component.[11] When assessing the short run effect of an output change, we need to make an assumption about the effect of trend growth. There are two natural candidates for the effect: The effect of a change in the trend component in the short run is either equal to the estimated effect of a change in the cycle component, or the effect is equal to zero.[12] The former assumption is routinely made in the context of ARDL models, but it is important to emphasise that the assumption made does not affect the results or interpretations on the long run in any way. Yet, it is interesting from the point of view of SWB analyses because it affects the interpretation of the short-run effects and, thus, adaptation. Therefore, we must examine the short run effects of GDP changes separately under the two assumptions.

Figure 1 presents two graphs of the short-run and long-run effects of the log of real GDP changes. The graph on the left assumes that the short-run effects of a change in the cycle component and in the trend component are equal. The graph on the right assumes that trend growth has a zero effect. In these graphs, we set trend growth to 2.1%, which is the average trend growth in our sample. The graph on the left points to adaptation to positive changes in output. So does the graph on the right once one takes into account the insignificance of the long run effect of a positive change. Notice that the graph on the right is in line with the idea that trend growth is classified as a foregone gain in the short run. Thus, trend growth is needed to keep SWB constant. This means that an economy not growing has a negative effect on SWB, but since trend growth is a foregone gain, the effect is not as strong as in the case of a loss (see Kahneman, Knetsch and Thaler, 1991). The foregone gain effect is adapted to in the long run. Losses, that is, negative changes in GDP, have visibly larger effects than GDP gains both in the short run and in the long run. The effects are mostly of similar magnitude, so we do not observe significant adaptation to losses. Overall, our results suggest that there is adaptation to the effects of positive changes in output. Negative changes, the effects of which are larger than those of positive changes, are not adapted to.

Our results so far come from our baseline NARDL specification (1), which is restrictive in the sense that no lags beyond the first are included. This means that we do not observe how the effects evolve over time. Moreover, our results suffer from omitted variables biases if the excluded lag variables are relevant and are correlated with the variables in the current model. In what follows, we augment model (1) by including more lags to it.

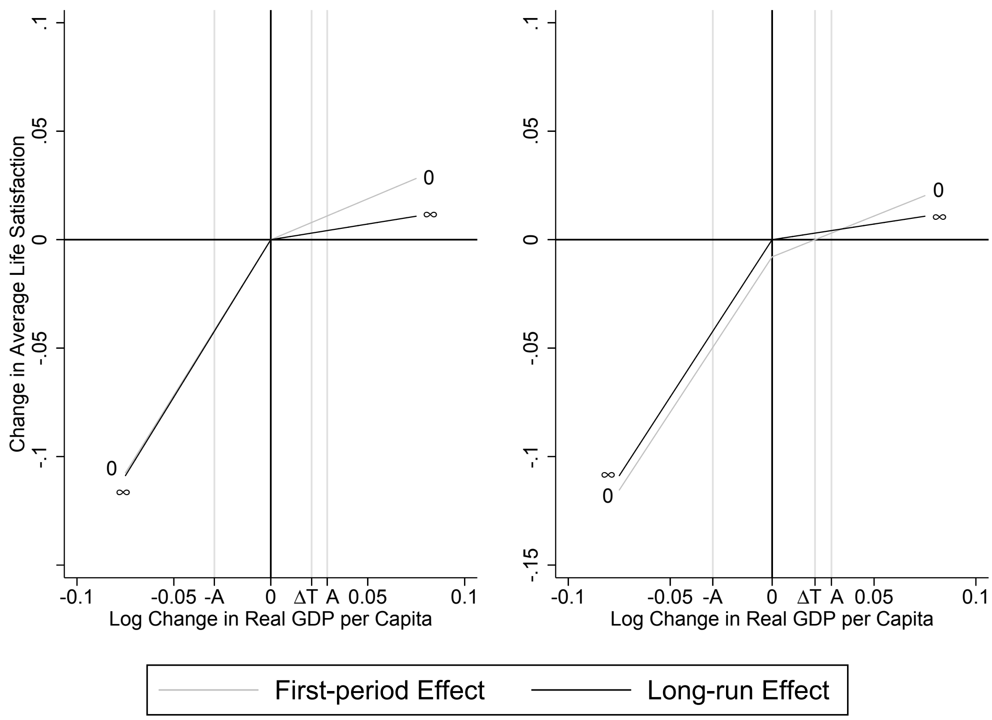
C. Results from a More Flexible Model

To allow for flexible short-run dynamics, previous studies examining adaptation to income changes have controlled for more lags of the explanatory variable. For example, Vendrik (2013) includes two lagged differences of the income variable in his ARDL model of life satisfaction. Lagged values of the explanatory variable have also been controlled for in models of SWB by Di Tella, MacCulloch, and Oswald (2003), Di Tella and MacCulloch (2008), and Di Tella, Haisken-De New, and MacCulloch (2010). These studies have estimated DL models in which

[11] See the appendix for a more thorough and formal discussion of these issues.

[12] A way to get information on the plausibility of the two assumptions is to rely on between-country variation. We regressed the average SWB in the sample countries on trend growth rate, and the resulting coefficient is negative and insignificant. This result points to the effect of trend growth being zero.

Figure 1: Relationship between Average Life Satisfaction and Log of Real GDP Changes



Left-hand panel: trend growth assumed to have an effect in the short run. Right-hand panel: trend growth assumed to have no effect in the short run. ΔT denotes the average trend growth of GDP in the sample (0.021) used to calculate the short-run effect sizes in the right-hand panel. A denotes the mean absolute growth of GDP in the sample (0.029). The lag associated with each line near the end of the line (the long-run effect is denoted by ∞).

each additional lagged level of the income variable allows for more flexibility in the short run but also a longer dynamic SWB process following an income change. In this section, we follow standard practice in estimating ARDL models by adding lagged first-differences of both the explanatory variable and the dependent variable into model (1). The number of lagged differences to be included is chosen according to the model selection procedure described below. We start the model selection by estimating a model of the general form

$$\begin{aligned} s_{i,t} = (1-\alpha)s_{i,t-1} + \sum_{j=0}^{q-1}(\beta_j \Delta y_{i,t-j} + \beta_j^{-} \Delta y_{i,t-j} D_{i,t-j}) + \sum_{j=1}^{p-1} \phi_j \Delta s_{i,t-j} \\ + \gamma \sum_{\tau=I_i}^{t-1} \Delta y_{i,\tau} + \gamma^{-} \sum_{\tau=I_i}^{t-1} \Delta y_{i,\tau} D_{i,\tau} + \lambda_i + \eta_t + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where $q = 4$ and $p = 4$. We first test the joint significance of β_3 and β_3^{-} and the significance of ϕ_3.[13] We then drop the variables associated with insignificance at the 10% level and re-run the model. Again, the significances of the longest lags are tested for and the redundant variables are dropped. This procedure is repeated until both the β and β^{-} for the longest lag of the GDP variables and ϕ for the longest lag of the life satisfaction variable are statistically significant. Following this procedure, we end up estimating a model with two lagged differences of output and three lagged differences of SWB. The results from estimating this model are reported in the second column of table 3. For comparison purposes, we have re-estimated the model in column 7 of table 2 using the smaller sample, and the results are presented in the first column of table 3. It can be observed from the first column that the results for the smaller sample are very similar to the results for the full sample.

Although many of our findings remain unaltered, employing the more flexible specification reveals that the short-run dynamics cannot be satisfyingly described by the simpler specification. The lower panel of table 3 presents the dynamic effects of national income changes on SWB over the first ten years and the long-run effects. It can be observed that, in fact, the effect of a positive output change does not start dissipating immediately after the first-year effect. Instead, the effect reaches its maximum in the second year, i.e., year after the output change has occurred. Other macro-level studies using Eurobarometer data have also found that the effect of an output change is largest in the year following the output change (Di Tella, MacCulloch, & Oswald, 2003; Di Tella & MacCulloch, 2008). This may be because many of the Eurobarometer surveys are conducted in the first half of the calendar year or because output change actually affects SWB with a lag. The effect of a positive output change is statistically significantly different from zero at the 10% level up until the ninth year after the output change. The 10th-year effect is not statistically significant, nor are the effects after that, based on further calculation.

The effects of a negative output change follow a somewhat different pattern, but as in the case of a positive output change, the first-year effect is not the largest effect. The effects become larger in the course of time, and they are statistically significantly different from zero in every year following the change and also in the long run. We also tested for effect asymmetry in each year. It was found that the effect of a negative output change is statistically significantly larger than the effect of a positive output change in every year except for the second year. As can be

[13] We want to minimise the loss of panel observations and thus set the maximum lag length for the differenced variables to 3, which means that we use GDP and life satisfaction information up to period $t-4$. By doing this, we lose 101 observations in total from our sample. We also experimented with maximum lag lengths of 4 and 5 but ended up with similar results. These results are available upon request.

Table 3. Models of Life Satisfaction: Additional Lags

	(1)		(2)	
s_{t-1}	0.73***	(0.04)	0.78***	(0.03)
Δs_{t-1}			-0.13***	(0.04)
Δs_{t-2}			-0.04	(0.04)
Δs_{t-3}			0.07*	(0.05)
Δy_t	0.53***	(0.15)	0.43**	(0.17)
Δy_{t-1}			0.83***	(0.21)
Δy_{t-2}			-0.49***	(0.18)
y_{t-1}	0.04	(0.03)	0.03	(0.03)
Δy_t^-	0.98***	(0.34)	0.81**	(0.35)
Δy_{t-1}^-			-0.68*	(0.36)
Δy_{t-2}^-			0.43	(0.39)
y_{t-1}^-	0.43***	(0.12)	0.33**	(0.13)
α	0.27***	(0.04)	0.22***	(0.03)
1st-year effect of Δy	0.53***	(0.15)	0.43**	(0.17)
2nd-year effect of Δy	0.43***	(0.12)	1.14***	(0.20)
3rd-year effect of Δy	0.36***	(0.10)	0.32*	(0.18)
4th-year effect of Δy	0.31***	(0.09)	0.39***	(0.15)
5th-year effect of Δy	0.27***	(0.10)	0.41***	(0.14)
6th-year effect of Δy	0.24**	(0.10)	0.29**	(0.13)
7th-year effect of Δy	0.22**	(0.10)	0.27**	(0.13)
8th-year effect of Δy	0.21*	(0.11)	0.25**	(0.13)
9th-year effect of Δy	0.19*	(0.11)	0.22*	(0.13)
10th-year effect of Δy	0.19*	(0.11)	0.21	(0.13)
$\vdots$				
Long-run effect of Δy	0.16	(0.12)	0.13	(0.15)
1st-year effect of Δy^-	1.51***	(0.11)	1.23***	(0.27)
2nd-year effect of Δy^-	1.59***	(0.12)	1.32***	(0.27)
3rd-year effect of Δy^-	1.64***	(0.26)	1.27***	(0.31)
4th-year effect of Δy^-	1.68***	(0.23)	1.45***	(0.29)
5th-year effect of Δy^-	1.71***	(0.24)	1.49***	(0.31)
6th-year effect of Δy^-	1.73***	(0.27)	1.52***	(0.35)
7th-year effect of Δy^-	1.75***	(0.30)	1.56***	(0.39)
8th-year effect of Δy^-	1.76***	(0.32)	1.58***	(0.43)
9th-year effect of Δy^-	1.77***	(0.34)	1.60***	(0.46)
10th-year effect of Δy^-	1.77***	(0.35)	1.62***	(0.49)
$\vdots$				
Long-run effect of Δy^-	1.79***	(0.40)	1.68***	(0.60)

Bias-corrected estimates. N = 573. Country and year fixed effects included in all regressions. Upper panel presents the coefficient estimates and lower panel presents the estimated effects and hypothesis testing. *, ** and *** denote significance at the 1%, 5% and 10% levels, respectively. Standard errors in parentheses are bootstrapped with 200 replications.

seen from table 3, the second-year effect of a positive output change is, in fact, slightly larger than the effect of a negative change.

As discussed earlier, we must excercise caution when interpreting the short-run results because we do not get an estimate of the short-run effect of trend growth. That is, the coefficients of the first-differenced output variables are only informative about the short-run effects of changes in the cyclical component of output. As was done in the case of figure 1, we now use the two alternative assumptions about the effect of trend growth in the short run. The dynamic effects of a positive and negative unit change in log of real GDP per capita over the first 30 years following the output change under the two assumptions are presented in figure 2.[14,15] The left-hand panel makes the assumption that the short-run effect of trend growth is the same as the short-run effect of a change in the cyclical component of output. Notice that this assumption was also implicitly made above when we interpreted the effect estimates in the lower panel of table 2 as the effects of output changes. The right-hand panel of figure 2 in turn makes the assumption that trend growth does not have any short-run effect. Black and gray lines show the effect estimates from the augmented model in column 2 of table 3 and, for comparison purposes, the baseline model in column 1 of table 3, respectively. Upper lines show the effects of a positive change and lower lines show the effects of a negative change.

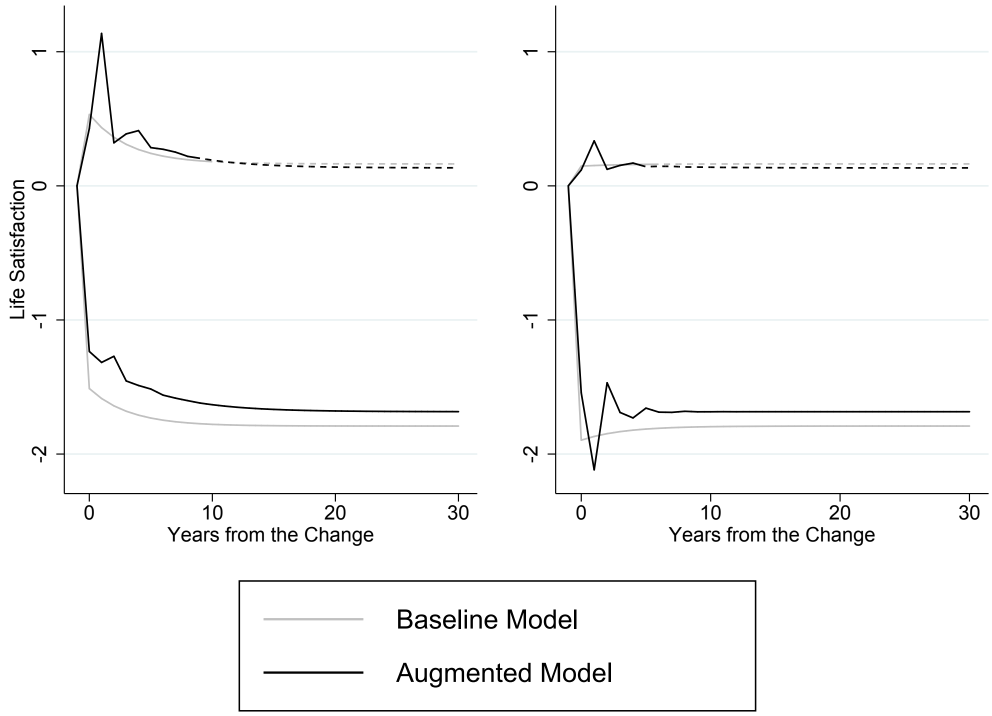
It can be seen by comparing the left-hand and right-hand panels of figure 2 that the many of the conclusions do not depend on what we assume about the short-run effect of trend growth. The effects of positive output changes are statistically significant for almost ten years, after which they become insignificant. Negative changes in turn have statistically significant effects in the long run as well. As mentioned above, there is marked effect asymmetry in about all years, the only exception being the second-year effects in the left-hand panel. In the right-hand panel, there is statistically significant asymmetry in the second year also. This is because, under the assumption of zero effect of trend growth, trend growth does not increase SWB in the case of a positive output change but the foregone-gain effect decreases it in the case of a negative change.

We can see at least some adaptation to positive output changes in both panels if we compare the sizes of the largest effect and the long-run effect. As has been done in earlier studies, we consider the fact that the effects become statistically insignificant over time a sign of adaptation. The result of significant short-run effects and an insignificant long-run effect is in line with the findings presented in the previous section and the findings from micro-level studies that use symmetric models (Vendrik, 2013; Di Tella, Haisken-De New, & MacCulloch, 2010). Whether there is adaptation to negative output changes depends on what is assumed about the short-run effect of trend growth. If we assume that trend growth has the same short-run effect as

[14]Because only the cyclical component of output has a short-run effect in the right-hand panel, we need to know how much of a unit change in output is cyclical. In our sample, the mean trend growth is 72% of the mean absolute GDP growth. Therefore, the cyclical component changes 0.28 for every positive "typical" (unit) change in output. In turn, the cyclical component changes -1.72 for every negative "typical" (unit) change in output. Notice, however, that in the case of a negative unit change in output, -0.72 is treated as a foregone gain and the remaining -1 is treated as a loss. We use these numbers to calculate the effects in the right-hand panel of figure 2. We advise the reader also to consult the appendix and the discussion related to figure 3 below to see how this works.

[15]The long-run effect of trend growth is set to equal the long-run effect of the cyclical component. This is what we found when we tried adding the trend component variable in models presented in columns 1 and 2 of table 3.

Figure 2: The Dynamic Effects of Positive and Negative GDP Changes on Life Satisfaction



Left-hand panel: trend growth assumed to have an effect in the short run. Right-hand panel: trend growth assumed to have no effect in the short run. Effects calculated for one-unit change of the log of real GDP per capita. In the right-hand panel, trend growth is set to about 0.72 units based on the average trend growth of GDP (0.021) being about 72% of the mean absolute growth of GDP (0.029) in the sample. Gray lines based on the results in column 1 of table 3. Black lines based on the results in column 2 of table 3. Solid (dashed) line indicates statistical significance (insignificance) at the 10% level.

the cyclical component (left-hand panel), the effect becomes larger over time. If trend growth is assumed to have no short-run effect (right-hand panel), the short-run effects of a negative change are larger due to the foregone-gains effect and some adaptation is observed after the second year. In any case, the effects of a negative output change are relatively large and statistically significant in the short run and in the long run. The persistence of the effect of a negative output change on life satisfaction is in line with the results presented in the previous section. This result is also in line with Clark, D'Ambrosio, and Ghislandi (2016) who show that there is no adaptation to poverty or to any income drop at the individual level. Although the magnitude of asymmetry in the effects of positive and negative changes varies over time and depends on the assumption made, we can say that asymmetry becomes more important over time. This is because positive changes have statistically significant effects only in the short run but the effects of negative changes are significant over the long run as well.

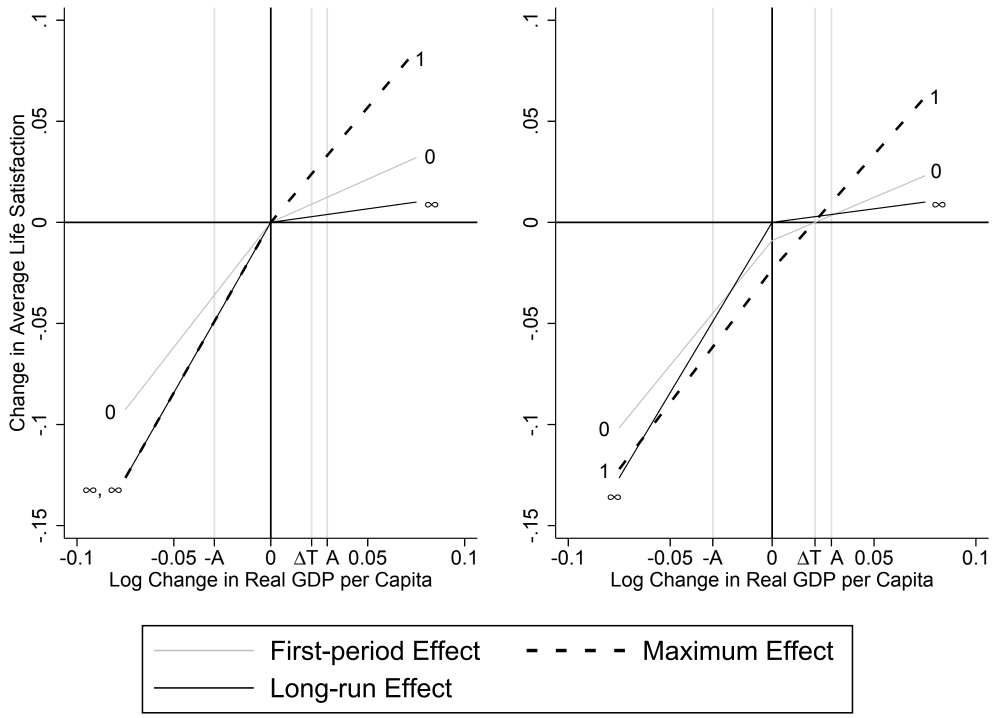
The dynamic effects presented in figure 2 are calculated for a "typical" output change in the sense that trend growth relative to the output change is fixed to correspond to the average trend growth relative to the average absolute growth in the data. Let us now look at the effects of output changes of different sizes. These are shown in figure 3 for the flexible model (column 2 of table 3). Assumptions about the effect of the trend growth in the left-hand panel and in the right-hand panel are the same as those in the left-hand panels and right-hand panels of figures 1 and 2.[16] In addition to the impact effects (gray lines) and the long-run effects (black lines), we have drawn the maximum effect (dashed line). We have determined the maximum effects based on calculating effects for "typical" positive and negative output changes, i.e., for 2.9% and -2.9%, respectively. Therefore, the years in which the maximum effects occur can be identified from figure 2 as well. The number at the end of each line denotes the lag, i.e., years passed from the output change.

As in figure 1, we can see the role of foregone gains in the right-hand panel. The effect asymmetry in the short run is larger when we assume the foregone gain effect, as in figure 2. In the right-hand panel, we also observe that for output drops larger than "typical"there is little to no adaptation to the maximum effect. Finally, if we use figure 3 to assess loss aversion in the long run, we can see that there are clear asymmetries in the effects of output changes of all sizes.

The results of the NARDL models presented in this and the previous section provide new evidence on the long-run effects of positive and negative output changes. In a previous study using Eurobarometer data, Di Tella and MacCulloch (2008), show that there is no significant long-run effect of an output change when the long-run effects of positive and negative output changes are assumed to be of equal size. Similar result has been found in studies using individual-level data (Di Tella, Haisken-De New, & MacCulloch, 2010; Vendrik, 2013). Our results show that the insignificant long-run effect holds for positive changes but not for negative changes. Our results thus indicate that the insignificant long-run effect found previously results from the insignificant long-run effect of positive changes. Furthermore, by observing strikingly different long-run effects of positive and negative output changes, we are able to show that the macro-level short-run asymmetries found by De Neve et al. (forthcoming) are persistent.

[16]It is easy to see that because the marginal effect is independent of the size of the output change under the assumption made in the right-hand panels, figure 3 does not give any additional information compared to figure 2 when it comes to the right-hand panels.

Figure 3: Relationship between Average Life Satisfaction and Log of Real GDP Changes



Left-hand panel: trend growth assumed to have an effect in the short run. Right-hand panel: trend growth assumed to have no effect in the short run. ΔT denotes the average trend growth of GDP in the sample (0.021) used to calculate the short-run effect sizes in the right-hand panel. A denotes the mean absolute growth of GDP in the sample (0.029). The 'Maximum effect' is the largest of the estimated effects (lags from zero to infinity) calculated at mean absolute growth A, or, in the case of negative changes, $-A$. The lag associated with each line near the end of the line (the long-run effect is denoted by ∞).

IV. Discussion and Robustness

A. Discussion

Our results indicate that the relationship between GDP and well-being is influenced by both adaptation to positive GDP changes and asymmetries. We also show that the short-run loss aversion observed in earlier macro- and micro-studies persists in the long run. Thus, we can confirm many of the findings of earlier studies, each of which looks at only one of the two phenomena. Ignoring the other of the two phenomena has had only the impact of failing to notice that there is no adaptation to income reductions. A notable exception to this is the recent paper by Clark, D'Ambrosio, and Ghislandi (2016) which focuses on adaptation to poverty and income reductions and is, therefore, able to find the no-adaptation result. Our findings emphasise that the correct strategy when studying the income-SWB relationship is to allow for both adaptation and loss aversion. Looking at the results from our simpler models reveals that allowing for adaptation but ignoring asymmetries can lead one to conclude that income changes do not matter in the long run (columns 3 and 4 in table 2). Ignoring adaptation but allowing for asymmetries, however, can lead one to ignore the possibly large variability in the effects over time (columns 5 and 6 in table 2). Furthermore, specifications should be flexible enough so that effect dynamics, such as the effects peaking only after some time has passed from the income change, can be observed (column 7 in table 2 vs. column 2 in table 3).

Although we are the first to document the larger long-run effects of negative than positive national income changes, results from some earlier studies points to such asymmetry. Wolfers (2003) has shown that business cycle volatility, measured by variation in unemployment, is harmful to well-being. Our results suggest that business cycles are harmful if they are associated with at least some national income reductions. A recent paper by Clark, D'Ambrosio, and Ghislandi (2015) present evidence for negative effects of poverty entries on individuals' well-being. These effects persist even after they have managed to exit poverty. Similarly, our results suggest that national income reductions have negative effects in the long-run, despite a period of recovery following the reductions. In addition to the above papers, various papers on hedonic adaptation find that people tend to adapt more to positive than to negative events, suggesting that people have a more general tendency to be loss averse in the long-run.

Given our results, it is interesting to examine how they can help us understand why, as originally noted in the United States by Easterlin (1974), nations' SWB levels do not seem to grow in the long run although the economies are growing. Based on statistical insignificance of the effect of a positive GDP change in the long run, one could argue that GDP growth has a zero long-run effect on SWB. In that case, SWB does not grow over time simply because people adapt completely to national income increases. However, because GDP per capita may measure social reference income, some part of this observed macroeconomic adaptation may be due to the presumably negative effect of others' income building up over time. Vendrik's (2013) results using a German individual-level panel point to these kinds of dynamics of social comparisons, whereas the effect of one's own income dissipates over time.

Further questions arise if we take the estimated long-run effect at face value and ignore its statistical insignificance. One interesting question is whether the estimated long-run loss aversion is strong enough for the effects of the negative GDP changes in the data to offset the effects of the positive changes, thus keeping SWB from rising in the long run. For example, Easterlin (2009) and De Neve et al. (forthcoming) have speculated about this, but ours seems to be the first analysis to provide results on the importance of loss aversion in the long run. We can apply the estimated coefficients of positive GDP changes (0.13) and negative GDP changes

(1.68) taken from column 2 of table 3 to the GDP changes in our data and see that, indeed, macroeconomic long-run loss aversion keeps SWB from rising. That is, the SWB gains from GDP growth in our sample are offset by the SWB losses from GDP reductions in our sample.

Given that long-run loss aversion is so strong, another interesting question is how macroeconomic adaptation contributes to it. Put differently, are the effects of positive and negative GDP changes such that, without any adaptation, the GDP changes in our data would actually improve SWB over the long run? To answer this question, we need to look at the maximum effects that positive and negative GDP changes have and assume that these effects are not diminished afterwards by adaptation. It appears that the answer depends on what we assume about the short-run effect of trend growth. The estimated effects of GDP changes of different sizes under the two alternative assumptions can be seen in figure 3. Assuming that trend growth has the same effect as deviations from it (left-hand panel), there is very little asymmetry in the maximum effects. In this case, should adaptation not diminish the effect of positive changes, GDP changes lead to positive development of SWB in the long run. If it were assumed that trend growth has a zero effect on SWB (right-hand panel) and, therefore, that growth falling short of trend growth has a negative foregone gain effect, the sum of positive effects would not be larger than the sum of negative effects. In this case, the result is no SWB growth in the long run, even without adaptation.

Based on the above discussion, it depends on the assumption made about the short-run effect of trend growth which of the two phenomena is the reason for non-increasing time profile of nations' SWB: either adaptation to the effects of positive GDP changes and no adaptation to the negative effects; or the effects of positive changes being relatively small already in the short run. Both of these would lead to the large long-run asymmetry that we find and, therefore, to no growth in SWB over time.

B. Robustness checks

Below we will discuss the results from different robustness checks for the NARDL model with lagged differences of SWB and GDP. In all of the robustness checks, we have chosen the number of lagged differences to be included based on the procedure described in Section III B.

Up until this point, we have used LSDVC as our preferred estimation method because of the Nickell bias. However, if we use standard least squares dummy variables (LSDV), we end up with results similar to the ones reported above. In the LSDV results, the coefficient of the lagged level of life satisfaction is around 0.7, which is smaller than in the LSDVC results, but the estimates of the long-run effects of positive and negative changes in output are of similar magnitude.[17]

Some studies that examine the relationship between GDP and SWB have controlled for some individual-level or macro-level control variables such as age, gender, employment status or the rate of unemployment (Di Tella, MacCulloch, & Oswald, 2003; Di Tella & MacCulloch, 2008; Stevenson & Wolfers, 2008; De Neve et al., forthcoming). Some of them do this to check the robustness of the results. Our paper belongs to the group of studies in which the focus is on the GDP-SWB relationship, and many of the control variables are seen as being determined by the economy, measured by GDP. In the case of such variables, like unemployment, the association between GDP and SWB is thus mediated through these variables. Although we do not study the

[17]When we use LSDV, we are able to use country-clustered standard errors that are not available in the LSDVC method. The choice of standard errors in LSDV does not affect the significance of the coefficients, however.

transmission mechanisms by including mediator variables in our models, some other variables can be controlled for. Age and gender (controlled for by e.g. Stevenson & Worlfers, 2008 in their analyses) are examples of variables that are likely not determined by GDP but may affect SWB. We have checked the robustness of our results to controlling for age and gender. Since the variable of interest, output, only varies at the country-year level, the individual-level variables capture the effect of within country changes in these control variables. For example, age controls can capture the effect of population aging over time. We tried controlling for age and gender by using a dependent variable from which the effects of these variables are removed.[18] Using this strategy, we find results almost exactly similar to the ones reported above, with no change in the significance of the reported coefficients.

When we use the bias-corrected least squares dummy variables method, we have to choose the accuracy of the bias approximation and the instrument set for the initial estimator. In the LSDVC results presented above, we have used bias approximation that is accurate to order $O(T^{-1})$. Although this should, on average, account for 90% of the true bias, also approximations with higher order terms are available for situations in which the number of cross-sectional units is not very large (Bruno, 2005). Furthermore, we have used all available lags as instruments for the initial estimator. Roodman (2009) argues that using all available lags for instruments may lead to biases which can be alleviated by using less instruments and, based on author's simulations, especially doing so by collapsing the instruments. Thus, any remaining bias in our estimates could be further reduced by using a more accurate bias approximation and reducing the number of instruments. To check robustness, we have estimated the model using bias approximation that is accurate to the (maximal) order of $O(N^{-1}T^{-2})$ and reducing the number of instruments from 450 to 39 by collapsing the instruments. We also tried changing the initial estimator from difference GMM to system GMM, again with the highest order bias approximation and collapsed instruments. These analyses yielded similar estimates as were obtained without the modifications. Most importantly, the estimated short-run and long-run effects of positive and negative changes and their statistical significances are similar, so our conclusions do not change.

V. Conclusions

Earlier studies of the effects of income on subjective well-being using micro data have found evidence for adaptation and loss aversion. Other studies have found that reflections of both phenomena can be observed in the relationship between national income and subjective well-being. We adopted an empirical framework which allows for both dynamic effects (adaptation) and asymmetries (loss aversion) to study the macro relationship. The approach has the advantage of avoiding biases arising from ignoring either adaptation or loss aversion. More importantly, the approach allows us to present first evidence of long-run asymmetries in the effects of national income on well-being.

Our findings are in line with what one would expect based on earlier studies. Positive changes in national income have effects on well-being in the short run but these effects wear off over

[18]To construct this new life satisfaction variable, we have regressed life satisfaction on country-year dummies controlling for three gender dummies (male, female, no answer), a quartic in age, a dummy for missing age, and interactions between the gender dummies and age variables. Using the estimated coefficients of the country-year dummies from this regression, we attain the average life satisfaction for each country-year controlling for the effects of gender and age.

time. Negative changes in national income are incompletely, if at all, adapted to. Thus, there is a long-run asymmetry in the effects of income changes.

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APPENDIX: Controlling for the trend component of output

A. Long run

Long-run effect estimates are obtained by including either the output variable (static models) or its lagged value (ARDL models) in the regression. Controlling the trend component of output (or its lag) allows trend growth and deviations from it to have different effects. Let us show this using our simplest model in which adaptation and loss aversion are not allowed for:

$$s_{i,t} = \gamma y_{i,t} + \lambda_i + \eta_t + \epsilon_{i,t}. \tag{A1}$$

The output variable y is a sum of its cyclical component and trend component:

$$y_{i,t} = C_{i,t} + T_{i,t}. \tag{A2}$$

If the two components have different effects on life satisfaction, the true model is

$$s_{i,t} = \gamma_C C_{i,t} + \gamma_T T_{i,t} + \lambda_i + \eta_t + \epsilon_{i,t}, \tag{A3}$$

which can be written as

$$s_{i,t} = \gamma_C (y_{i,t} - T_{i,t}) + \gamma_T T_{i,t} + \lambda_i + \eta_t + \epsilon_{i,t}, \tag{A4}$$

and, further, as

$$s_{i,t} = \gamma_C y_{i,t} + (\gamma_T - \gamma_C) T_{i,t} + \lambda_i + \eta_t + \epsilon_{i,t}. \tag{A5}$$

Thus, including the trend component in a model with the output variable as the regressor allows the trend component and the cyclical component to have different effects on life satisfaction. Testing the statistical significance of the coefficient $(\gamma_T - \gamma_C)$ then tests the difference of the effects of the two components. For example, in an intuitive special case in which trend growth does not have any effect on life satisfaction in the long run ($\gamma_T = 0$), zero output growth has a (negative) foregone gain effect of $-\gamma_C$.

It is easy to see that the same logic applies to dynamic models, although in such cases, the lagged trend component is controlled for.

Let us now consider the implications of controlling for the trend component in the case of asymmetries. The model is the one that allows for asymmetries but not adaptation:

$$s_{i,t} = \gamma y_{i,t} + \gamma^- y^-_{i,t} + \lambda_i + \eta_t + \epsilon_{i,t}. \tag{A6}$$

Again, dividing y into the two components and using the above manipulations gives us

$$s_{i,t} = \gamma_C y_{i,t} + (\gamma_T - \gamma_C) T_{i,t} + \gamma^- y^-_{i,t} + \lambda_i + \eta_t + \epsilon_{i,t}, \tag{A7}$$

which is the original asymmetries model but controlling for the trend component. An important feature of the model is that the long-run effect of an output change approaches $(\gamma_T - \gamma_C)\Delta T_i$ as the output change approaches zero, both from the right and from the left. This is a desirable property because, although we want to allow asymmetry around zero growth, we do not want to allow for any discontinuities in the effect function. In the special case of trend growth having a zero (long-run) effect (that is, γ_T = 0), if growth falls short of trend growth, this shortfall is a foregone gain instead of a loss.

Again, it is easy to see that the same logic applies to dynamic models.

B. Short run

Let us first look at our simplest dynamic model, that is, the one with no asymmetries and a lag length of 1:

$$s_{i,t} = (1-\alpha)s_{i,t-1} + \beta\Delta y_{i,t} + \gamma y_{i,t-1} + \lambda_i + \eta_t + \epsilon_{i,t}. \tag{A8}$$

We have already discussed controlling for the lagged level of the trend component of output. Imagine now that the effects of the cyclical and the trend component are different in the short run. Short-run effects are captured by coefficients of the differenced variables. Because trend growth is a country-specific constant and its effect is, therefore, absorbed by the country fixed effect, we cannot get an estimate of its (short-run) effect. If Δy is decomposed into change in the cyclical component and trend growth, the model becomes

$$s_{i,t} = (1-\alpha)s_{i,t-1} + \beta_C\Delta C_{i,t} + \beta_T\Delta T_{i,t} + \gamma y_{i,t-1} + \lambda_i + \eta_t + \epsilon_{i,t}, \tag{A9}$$

which can be written as

$$s_{i,t} = (1-\alpha)s_{i,t-1} + \beta_C\Delta y_{i,t} + (\beta_T - \beta_C)\Delta T_{i,t} + \gamma y_{i,t-1} + \lambda_i + \eta_t + \epsilon_{i,t}. \tag{A10}$$

From these it can be seen that, due to the fact that trend growth cannot be included, we get the same short-run effect estimate regardless of whether we include the change in output or the change in its cyclical component as a regressor. The estimate is, in both cases, an estimate of the effect of a change in the cyclical component. This is the reason why we need to make an assumption about the short-run effect of trend growth to get an estimate of the short-run effect of an output change.

As in the long run, the short run effect of trend growth determines the annual constant effect on life satisfaction. The short-run effects have the same properties (described above) as the long-run effects.