The Causal Relationship between Happiness and Smoking: A Bootstrap Panel Causality Test*

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ABSTRACT

This study applies the recently developed bootstrap panel causality test proposed by Kónya (2006) to investigate the causal link between happiness and smoking using per capita cigarette consumption and happiness index for 5 countries (i.e. Japan, France, Germany, the UK, and the US) over the period of 1961-2003. A key feature of the bootstrap panel causality is that it is more robust than other methods due to the generation of country-specific critical values from the bootstrapping method. Empirical results show a feedback for both Japan and France and independence for the other 3 countries. These results indicate smoking make people happy. However, in both Japan and France people smoke less if they feel happy. To reduce the omitted variable bias, we also added per capita real GDP as a control variable in our study over the 1969-2003 period. When doing this the empirical results show a feedback for France, a one-way Granger causality running from happiness to cigarette consumption for both Japan and the UK, and independence for the other 2 countries, Germany and the US. These results indicate smoking make people happy in France. However, in Japan, France and the UK people smoke less if they feel happy.

Keywords; Happiness; Smoke; Bootstrap Panel Causality Test

JEL: C32, C33, I19

1. Introduction

Over the past several years, many studies have been devoted towards exploring the

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relationship between happiness and economic factors such as unemployment, income, and inequality (see, i.e., Ohtake, 2012; Lee et al., 2013; Ramos, 2014). However, with the exception of Moore (2009), none have been done on the causal link between happiness and smoking behaviour.

The study of the causality between smoking and happiness remains an important issue for policymakers who have for years introduced taxes, bans or other laws to reduce smoking as the links between smoking and health has been thoroughly explored and the negative externalities pointed out (Chaloupka et al. 1995, Budak et al., 2006; Goyel and Nelson, 2006; Goyel, 2007). In light of the negative health effects, which is public knowledge, the question remains as to why then people smoke? One possible reason as investigated by Moore (2009) is that smoking could lead to happiness. But its is also possible that the causality can run the other way round.

Against this backdrop, ourstudy makes the first attempt to study the causal nexus between smoking and happiness using data for Japan, France, Germany, the UK and the US over the period 1961-2003. We apply the bootstrap panel causality method proposed by Kónya (2006) in order to measure the determinants of causality between smoking and happiness. Note that Moore's (2009) analysis was based on a panel of survey data for British households. Though informative, we believe cross-country studies like ours is likely to provide more information, since economic conditions and cultures vary more across countries, than within a single country.

The rest of this paper is organized as follows: Section 2 contains a literature review, section 3 presents the data used in this study while Section 4 describes the bootstrap panel Granger causality test proposed by Kónya (2006). Section 5 presents our empirical results and Section 6 concludes the paper.

2. Theoretical Background and Literature Review

As we know that both smoking and happiness can affect long-term health and the relationship between happiness and smoking is a complex issue (Moore, 2009). Empirical evidence suggests that smoking can act as a coping measure when perceived levels of stress increase (Kassel et al., 2003). Depressed smokers are less likely to quit (Anda et al., 1990) and cessation can promote depression (Covey et al., 1997). However, on the other hand, Goel (2014) found that greater economic stress will lower cigarette smoking.

Smokers who are in periods of abstinence may have reduced levels of happiness when compared to their non-smoking peers (Dawkins et al., 2007) but ex-smokers who have stopped for a year or more are happier than current smokers and similar to never smokers (Shabab and West, 2012).

As we know that smoke is harmful to health and could kill people, however, there are still a lot of people that like to smoke. Why do people smoke? Based on previous research, there are four reasons that people smoke. First of all, most smokers start smoking at his or her young age. The main reason is that a teenager smokes because young people feel smoking makes them look mature. Since teenagers see older people around them smoking, especially their parents and relatives, they smoke to act like the elderlypeople they see around them. If their friends or peers smoke, they may feel pressurized into behaving the same way. The second reason is the excitement of experimenting with something which is forbidden. In most countries, it is against the law for anyone under 18 years of age to smoke. Usually parents do not allow their under age teenagers to smoke as well. Therefore, smoking becomes very attractive. It is exciting to get cigarettes and sneak away to smoke without being caught. However, adults smoke for some other reasons. They may have a lot of stress and pressure because of economic and personal problems. They may be unemployed or working without making enough money to take care of themselves and their families. They may be homeless, or they may be dealing with alcohol or cocaine/heroin addictions. Some may be in bad marriages or relationships in which there is physical and/or verbal abuse. All these people may smoke to feel relaxed or to give them energy while going through a hard time.

Whether young or old, some people smoke to control their weight. Smokers, on average, weigh seven pounds less than non-smokers. Smoking reduces a person's appetite. It lessens his/her sense of taste and smell. This could be why ex-smokers gain weight after quitting cigarettes. Finally, there are people who say they love to smoke because smoking gives them pleasure. It just makes them feel good. Shahab and West (2012) finds that ex-smokers are happier than current smokers among Chinese adults in Hong Kong. Fidler and West (2011) also point out that enjoyment and addiction are the two major reasons why people continue to smoke despite the ever-evident health hazard.

Our study focuses on the last reason to see whether smoking makes people happier or happier people tends to smoke more by employing a boostrap panel Granger causality test proposed by by Kónya (2006) using data from Japan, France, Germany, the UK, and the US over 1961 to 2003.

3. Data

We used annual data for per capita consumption and happiness index for Japan, France, Germany, the UK and the US over the period of 1961-2003. Data for per capita cigarette consumption is from the Earth Policy Institute data centre and is available for download at: http://www.earth-policy.org/data_center/C26. Data for the Happiness Index is measured in terms of average level of life satisfaction and is sourced from the Trend in Nations from the World Database of Happiness.

Table 1. Summary Statistics of Cigarette Consumption Per Person

country	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.-B.
Japan	2397.23	2743.70	1419.97	372.60	-1.29	3.39	12.29***
France	1487.17	1749.50	1044.10	208.60	-0.68	2.39	4.04
Germany	1805.25	2089.89	1319.36	194.83	-0.81	2.84	4.77*
United Kingdom	1920.30	2521.14	1248.92	381.57	-0.07	1.59	3.55
United States	2380.58	2872.04	1544.78	424.08	-0.68	1.92	5.45*

Note: 1. The sample period is from 1961 to 2003.

2.***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table 2. Summary Statistics of Happiness Index

Country	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.-B.
Japan	39.80	44.80	31.54	3.00	-0.53	3.12	2.05
France	39.50	43.83	35.35	2.02	-0.43	2.46	1.88
Germany	40.01	44.63	36.33	2.85	0.14	1.45	4.41
United Kingdom	42.23	48.18	39.19	1.88	0.99	4.75	12.60***
United States	31.56	41.17	28.86	3.21	1.79	5.08	30.94***

Note: 1. The sample period is from 1961 to 2003.

2.***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table 1 reports summary statistics of per capita cigarette consumption for each country. We can see that Japan and France have the highest and lowest mean per capita cigarette consumption of 2, 397.23 and 1487.17, respectively. Table 2 reports summary statistics of the happiness index for each country. We can see that the UK and the US have the highest and lowest mean happiness index of 42.23 and 31.56, respectively. This means that, during the period under study, the UK was the happiest country and the US the least happy country among our sample countries.

Table 3 reports summary statistics of per capita real GDP for each country. We found that the US and Germany have the highest and lowest mean per capita real GDP of US$30,363.04 and US$25,053.14, respectively. Jarque-Bera test results also indicate that all the data series are normal, with the exception of per capita cigarette consumption in Japan.

Table 3. Summary Statistics of GDP

Country	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J.-B.
Japan	25429.34	34076.53	14485.51	6884.62	-0.12	1.44	3.59
France	25260.28	32788.06	16327.57	4687.93	-0.10	2.04	1.38
Germany	25053.14	32940.29	16071.73	5257.63	-0.02	1.71	2.40
United Kingdom	25244.53	36235.77	17448.59	5535.01	0.43	2.04	2.44
United States	30363.04	42002.23	21160.40	6475.43	0.28	1.88	2.30

Note: 1. The sample period is from 1969 to 2003.

2.***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

4. Methodology

4.1. Bootstrap Panel Causality Test.

We applied the bootstrap panel causality method proposed by Kónya (2006) [1] in order to measure the determinants of causality between smoking and happiness. As emphasized by Kónya (2006),[2] the results of the bootstrap panel causality method unit root test and cointegration test are all robust. This implies that not all variables need to be tested for stationary series properties. The robust feature of bootstrap panel causality arises from the generation of country-specific critical values from the bootstrapping method. It is important to note here that the variable levels used in empirical analysis play crucial roles in determining causal linkages because differencing variables to make them stationary (i.e. using the difference form of variables) may lead to a loss of trend dynamics in the series.

The bootstrap panel causality approach of Kónya first requires estimating the described system by SUR to impose zero restrictions for causality by the Wald principle, and then requires generating bootstrap critical values. Since country specific

[1] We refer to Kónya (2006) for more details of the bootstrapping method and of country-specific critical values.

[2] The alternative panel Granger causality test was developed by Hurlin (2008). The method controls for unobservable heterogeneity in panel data, but not for heterogeneity problems in cross-sectional data.

Wald tests with country specific bootstrap critical values are used in the panel causality method, the Wald test does not require a joint hypothesis for all countries in the panel.

The equation system for panel causality analysis includes two sets of equations that can be written as:

$$\begin{aligned}
PCC_{1,t} &= \alpha_{1,1} + \sum_{i=1}^{ly_1} \beta_{1,1,i} PCC_{1,t-i} + \sum_{i=1}^{lx_1} \delta_{1,1,i} HI_{1,t-i} + \varepsilon_{1,1,t} \\
PCC_{2,t} &= \alpha_{1,2} + \sum_{i=1}^{ly_1} \beta_{1,2,i} PCC_{2,t-i} + \sum_{i=1}^{lx_1} \delta_{1,2,i} HI_{2,t-i} + \varepsilon_{1,2,t} \\
&\vdots \\
PCC_{N,t} &= \alpha_{1,N} + \sum_{i=1}^{ly_1} \beta_{1,N,i} PCC_{N,t-i} + \sum_{i=1}^{lx_1} \delta_{1,N,i} HI_{1,N,t-i} + \varepsilon_{1,N,t}
\end{aligned} \tag{1}$$

and

$$\begin{aligned}
HI_{1,t} &= \alpha_{2,1} + \sum_{i=1}^{ly_2} \beta_{2,1,i} PCC_{1,t-i} + \sum_{i=1}^{lx_2} \delta_{2,1,i} HI_{1,t-i} + \varepsilon_{2,1,t} \\
HI_{2,t} &= \alpha_{2,2} + \sum_{i=1}^{ly_2} \beta_{2,2,i} PCC_{2,t-i} + \sum_{i=1}^{lx_2} \delta_{2,2,i} HI_{2,t-i} + \varepsilon_{2,2,t} \\
&\vdots \\
HI_{N,t} &= \alpha_{2,N} + \sum_{i=1}^{ly_2} \beta_{2,N,i} PCC_{N,t-i} + \sum_{i=1}^{lx_2} \delta_{2,N,i} HI_{N,t-i} + \varepsilon_{2,N,t}
\end{aligned} \tag{2}$$

In the equation systems (1) and (2), *PCC* refers to the indicator of per capita cigarette consumption, *HI* denotes the indicator of Happiness Index, *N* (=5) is the number of panel members, *t* is the time period *(t=1,…,T)*, and *l* is the lag length. In this regression system, each equation has different predetermined variables and the error terms might be cross-sectionally correlated; hence we can view these sets of equations as an SUR system. To test for Granger causality in this system, alternative causal relations for each country are likely to be found: (i) there is one-way Granger causality from *HI* to *PCC* if not all $\delta_{1,i}$ are zero, but all $\beta_{2,i}$ are zero; (ii) there is one-way Granger causality from *PCC* to *HI* if all $\delta_{1,i}$ are zero, but not all $\beta_{2,i}$ are zero; (iii) there is two-way Granger causality between *HI* and *PCC* if neither $\delta_{1,i}$ nor $\beta_{2,i}$ are zero; (iv) there is no Granger causality between *HI* and *PCC* if all $\delta_{1,i}$ and $\beta_{2,i}$ are zero.

Before proceeding with the estimation, the optimal lag lengths must be determined.[3] Since the results from the causality test may be sensitive to the lag structure, determining the optimal lag length(s) is crucial for the robustness of the empirical findings. In a large panel system, lag lengths and numbers of independent variables can cause a substantial computational burden. Following Kónya (2006), maximal lags are allowed to differ across variables but need to be the same across equations. In our paper, the regression system is estimated by each possible pair of ly_1, lx_1, ly_2, and lx_2; we assume 1 to 4 lags exist, and then we choose the combinations that minimize the Schwarz Bayesian Criterion[4].

4.2. Cross-Sectional Dependence and Slope Homogeneous Tests

One of the important assumptions in the bootstrap panel causality is the existence of cross-sectional dependence among the countries in the panel. In the case of cross-sectionally correlated errors, the estimator from the regression system described with the SUR is more efficient than the estimator with the pooled ordinary least squares (pooled OLS) model because the country-by-country OLS approach does not consider cross-sectional dependence. Therefore, testing for cross-sectional dependence is the most crucial issue for the selection of an efficient estimator, and

[3] Kónya (2006) pointed out this is an important step because the causality test results may depend critically on the lag structure. In general, lag decisions may cause different estimation results. Too few lags means that some important variables are omitted from the model and this specification error will usually cause incorrect estimation in the retained regression coefficients, leading to biased results. On the other hand, too many lags will waste observations and this specification error will usually increase the standard errors of the estimated coefficients, leading to inefficient results. Also, T should be greater than N.

[4] To save space, results from the lag selection procedure are not showed in the paper but are available upon the reader's request.

hence, for the panel causality results. Another important aspect of the bootstrap panel causality approach is testing for cross-country heterogeneity. A normal approach to testing the null hypothesis of slope coefficient homogeneity against the alternative hypothesis is to apply the Wald principle. The Wald principle is valid for cases where the cross-sectional dimension (*N*) is relatively small and the time dimension (*T*) of the panel is large; the explanatory variables are strictly exogenous, and the error variances are homoscedastic. Interested readers can refer to *Chang et al*., (2014) and *Pan et al., (2014)* for details about the cross-sectional dependence and slope homogeneous tests.

5. Empirical Results

5.1. Cross-sectional dependence and slope homogeneity

As outlined earlier, testing for both cross-sectional dependence and slope homogeneity in the bootstrap panel causality analysis is crucial for selecting the appropriate estimator and for imposing restrictions on causality. Accounting for cross-sectional dependence in empirical analysis is critical as countries are highly integrated and have a high degree of globalization in economic relations. Therefore, our empirical study starts by examining the existence of cross-sectional dependence and heterogeneity across the 5 countries. To investigate the existence of cross-sectional dependence, we carried out two different tests: CD (Breusch and Pagan, 1980) and LM_{adj} (Pesaran et al., 2008). Based the results from Table 4, it is clear that the null hypothesis of no cross-sectional dependence is rejected at the conventional levels of significance for both without and with GDP as a control variable. Therefore, the SUR method is more appropriate than the country-by-country pooled OLS method, which is assumed[5] by the bootstrap panel causality approach.

[5] The cross-sectional dependence furthermore implies that examining the causality between per capita cigarette consumption and happiness in these 5 countries requires accounting for this information in

Table 4. Cross-sectional Dependence and Homogeneous Tests without and with GDP as a control variable

CD	2.129* and 3.11*
LM_{adj}	15.606*** and 18.221**
$\tilde{\Delta}$	35.372*** and 36.11
$\tilde{\Delta}_{adj}$	2.103* and 2.32*

Notes: 1. The second entries in column two corresponds to the case where GDP is included as a control variable

2. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

Results from the slope homogeneity tests of Pesaran and Yamagata (2008) also reject the null hypothesis of the slope homogeneity hypothesis (see Table 4); thus, reports support country-specific heterogeneity (for both tests of $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$) for both without and with GDP as a control variable. The rejection of slope homogeneity implies that if the panel causality analysis imposes homogeneity restrictions on the variable of interest, there will be misleading inferences. Therefore, the final result of causality between happiness and per capita cigarette consumption may differ across the selected countries. The existence of cross-sectional dependence and heterogeneity across the 5 countries supports our claim about the suitability of the bootstrap panel causality approach.

5.2. Causality

The final results from the bootstrap panel Granger causality analysis are reported in

estimations of causality regressions. In the presence of cross-sectional dependence, the SUR approach is more efficient than the country-by-country OLS method (Zellner, 1962). Therefore, the estimation results obtained from the SUR model developed by Zellner (1962) are more reliable than those obtained from the country-specific OLS estimation.

Table 5. Cigarette Consumption does not Granger Cause Happiness

Country	coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
Japan	0.029	**4.508***	3.699	5.357	9.125
France	0.041	**3.686***	3.476	5.351	9.771
Germany	0.002	0.001	3.410	5.126	8.579
United Kingdom	-0.008	0.762	3.375	4.900	7.759
United States	0.006	0.170	3.562	5.053	8.977

Notes: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.

2. Bootstrap critical values are obtained from 10,000 replications.

Table 6. Happiness does not Granger Cause Cigarette Consumption

Country	coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
Japan	-0.363	**12.924***	3.369	5.242	8.073
France	-0.315	**9.052***	3.525	4.972	7.579
Germany	-0.092	1.004	3.694	5.142	9.636
United Kingdom	-0.040	0.079	3.410	4.943	9.607
United States	0.027	0.232	3.370	4.942	8.451

Notes: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.

2. Bootstrap critical values are obtained from 10,000 replications.

Tables 5-6.[6] Results indicate that a feedback between happiness and per capita cigarette consumption exist for both Japan and France (the countries with the most and least cigarette consumption). For the other three countries we find independence between happiness and per capita cigarette consumption. These results indicate no significant relationship exists between happiness and per capita cigarette consumption in these three countries. If we look at the coefficients and sign of both equations (1) and (2) for Japan and France, we find that cigarette consumption did increase the

[6] For the bootstrap procedure on how the country specific critical values are generated, interesting readers can refer to Kónya (2006).

happiness of people because the coefficients from equation (2) are significantly positive. This means that smoking can acts as a coping measure when perceived levels of stress increase and make people feel happier after they smoke. On the other hand, if we look at the coefficients from equation (1), they are both significantly. These results indicate that people smoke less when they feel happy. This result is consistent with that of Moore (2009) in that happier smokers tend to smoke less.

5.3. Robustness check

To reduce the omitted variable bias in our analysis we also add per capita real GDP as

Table 7. Cigarette Consumption does not Granger Cause Happiness with GDP as a Control Variable

Country	coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
Japan	0.043	1.750	3.620	5.121	9.526
France	0.086	**6.067****	3.769	5.481	9.618
Germany	0.007	0.005	3.751	5.405	10.687
United Kingdom	0.004	0.135	3.592	5.193	9.669
United States	0.012	0.602	3.485	4.882	8.153

Notes: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.
2. Bootstrap critical values are obtained from 10,000 replications.

Table 8. Happiness does not Granger Cause Cigarette Consumption with GDP as a Control Variable

country	coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
Japan	-0.378	**12.574*****	3.712	5.284	9.344
France	-0.324	**14.929*****	3.672	5.376	9.444
Germany	-0.554	0.324	3.929	5.513	10.419
United Kingdom	-0.618	**5.242***	4.003	5.885	10.418
United States	-0.025	0.016	3.677	5.311	7.788

Notes: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.
2. Bootstrap critical values are obtained from 10,000 replications.

a control variable in our study as the relationship between per capita real GDP and happiness is well understood. The results from the bootstrap panel Granger causality analysis are reported in Tables 7-8.

These results indicate that there exists a feedback between happiness and per capita cigarette consumption for France (the country with the least cigarette consumption), one-way Granger causality running from happiness to cigarette consumption for both Japan and the UK, and independence for the other 2 countries namely Germany and the US. If we look at both the coefficients and sign of equation (1) for France, we find that cigarette consumption did increase happiness because we find the coefficients from equation (1) are both significantly positive. On the other hand, if we look at the coefficients from equation (2) for Japan, France and the UK, they are significantly negative. These results indicate that happy people smoke less or people smoke less as they become happier. Of course, our results need to be interpreted with caution because what we find here is an average concept. As pointed out by Shahab and West (2012) that there might exist difference in happiness among smokers, ex-smokers and non- smokers. Future study will be in this direction.

6. Conclusions

This study tests whether people feel happy after they smoke or happier smokers smoke less using per capita cigarette consumption and happiness index for 5 countries (i.e., Japan, France, Germany, the UK, and the US) over the 1961-2003 period. We apply a recently developed bootstrap panel causality test, proposed by Kónya (2006) to investigate this issue. Empirical results show a feedback for both Japan and France and independence for the other 3 countries. In both Japan and France our results indicate that smoking does make people happy, however, if people feel happy, they reduce their cigarette consumption.

To reduce the omitted variable bias in our analysis we also add per capita real GDP as a control variable in our study. Upon doing this, our empirical results show a feedback effect for France, a one-way Granger causality running from happiness to cigarette consumption for both Japan and the UK, and independence for the other 2 countries. These results indicate smoking does cause people to be happier in France, however, if people are happier they smoke less in Japan, France and the UK. These results are in line with the findings of Anda et al., (1990) in that unhappy smokers are less likely to quit, but are in contrast regarding the direction of causality with the findings of Shabab and West (2012), where the authors found that ex-smokers who have stopped for a year or more are happier (Shabab et al., 2012). In general however, happiness can cut down on smoking.

The differences between the results across the countries suggest that there does not exists a single blanket policy that would work for each of the countries under consideration. In fact, policy makers should carry out careful economic analysis before deciding on a policy stance in terms of smoking, rather than making policy choices based on available information of some other country. For the majority of the countries (i.e. Japan, France and the UK) however, a major policy implication of our study is that to reduce smoking, an important consideration for policymakers should be that they create a happy environment and make people feel happier, since smoking could then automatically be reduced, and thus minimize the widely evidenced health hazards associated with smoking.

References

Anda, R. F., Williamson, D. F., Escobedo, L. G., Mast, E. E., Giovino, G. A. & Remington, P. L. (1990). Depression and the dynamics of smoking: A national perspective, *Journal of the American Medical Association*, 264, 1541–5.

Breusch, T. S. & Pagan, A. R. 1980. The Lagrange Multiplier test and its applications to model specification in econometrics. The Review of Economic Studies 47(1), 239-253.

Budak, J., Goel, R.K., and Nelson, J. (2006). Smoking Prevalence and Antismoking Regulations in Transition Countries, Transition Studies Review, 13(1), 231-248.

Chaloupka, F. J., Cook, P. J., Manning, W. G., Newhouse, J. P., Novotny, T. E., Shelling, T. C., Townsend, J., Warner, K. E. (1995). Criteria for determining an optimal cigarette tax: the economist’s perspective, *Tobacco Control*, 5:380-386

Chang, T., Lee, C. C., & Chang, C. H. (2014). Does insurance activity promote economic growth? Further evidence based on bootstrap panel Granger causality test. *The European Journal of Finance*, *in press*, http://dx.doi.org/10.1080/1351847X.2012.757555.

Covey, L. S., Glassman, A. H. & Stetner, F. (1997). Smokers with a history of depression have a lower likelihood of successfully quitting, and for those who quit, depression is more apt to be a prominent withdrawal symptom, American Journal of Psychiatry, 154, 263–5.

Fidler, J. A., and West, R. (2011) Enjoyment of smoking and urges to smoke as predictors of attempts and success of attempts to stop smoking: a longitudinal study, Drug and Alcohol Dependence, 115 (1-2), 30-34.

Goel, R.K. and Nelson, M. (2006). The Effectiveness of Anti-Smoking Legislation: A Review, Journal of Economic Surveys, 20(3), 325-355.

Goel, R. K. (2007) Costs of Smoking and Attempts to Quit, Applied Economics, 39(7), 853-857.

Goel, R. K. (2014) Economic stress and cigarette smoking: evidence from the United States, Economic Modelling, 40, 284-289.

Hurlin, C. (2008). Testing for Granger Non Causality in Heterogeneous Panels, Mimeo. Department of Economics: University of Orleans.

Kassel, J. D., Stroud, L. R. & Paronis, C. A. (2003). Smoking, stress, and negative affect: Correlation, causation, and context across stages of smoking, *Psychological Bulletin*, 129, 270–304.

Kónya, L. (2006). Exports and growth: granger causality analysis on OECD countries with a panel data approach. *Economic Modelling*, 23, 978–992.

Lee, C. G., Ng, P. K., & Lee, C (2013). Short run and long run causalities between happiness, income and unemployment in Japan, *Applied Economics Letters*, 20, 18, 1636-1639.

Moore, S. C. (2009) The nonpecuniary effects of smoking cessation: happier smoker smoke less, *Applied Economics Letters*, 16, 395-398.

Ohtake, F. (2012). Unemployment and happiness, *Japan Labor Review*, 9, 59–74.

Pan, C., Chang, TY. and Yemane, Wolde-Rufael (2014). Military spending and economic growth in the Middle East countries: Bootstrap panel causality test. *Defence and Peace Economics, in press,* http://dx.doi.org/10.1080/10242694.2014.891356.

Pesaran, M. H., Ullah, A., & Yamagata, T. (2008). A bias-adjusted LM test of error cross-section independence. *Econometrics Journal* 11*, 105–127.*

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics* 142, 50–93

Ramos, X (2014). Inequalities and happiness, J*ournal of Economic Survey, (in press).* doi: 10.1111/joes.12049.

Shahab, L., West, R. (2012). Differences in happiness between smokers, ex-smokers and never smokers: cross-sectional findings from a national household survey, *Drug and Alcohol Dependendce* 121, 1-2, 38-44

Zellner, A. (1962). An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias, *Journal of the American Statistical Association* 57, 348-368.