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ABSTRACT

Smoking and the Business Cycle: Evidence from Germany*

In this paper, we use data from the German Socio-Economic Panel to investigate the effect on cigarette consumption of macro-economic conditions in the form of regional unemployment rates. The results from our panel data models, several of which control for selection bias, indicate that the propensity to become a smoker increases significantly during an economic downturn, with an approximately 0.7 percentage point increase for each one percentage point rise in the unemployment rate. Conversely, conditional on the individual being a smoker, cigarette consumption decreases during recessions, with a one percentage point increase in the regional unemployment rate leading to an up to 0.8 percent decrease in consumption.

JEL Classification: E32, I12, J22

Keywords: business cycle, smoking, unemployment

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1 Introduction

Even though smoking causes millions of deaths worldwide, Germany has one of the highest prevalence of smoking among industrialized countries, with about 26 percent of the population and 30 percent of those aged 15-24 years being smokers (World Health Organization, 2016). In 2003, for example, 114,647 deaths and 1.6 million years of potential life lost were attributable to smoking, for a total cost of €21 billion (Neubauer et al., 2006). In parts of Germany (especially the former East Germany), smoking among women has tripled since the 1989 demolition of the Berlin Wall. Hence, even though all WHO members have adopted a voluntary global target of a 30 percent reduction in tobacco use by 2025, WHO trend analyses indicate that Germany will not achieve this goal.

Given these statistics, it is important to understand what determines cigarette consumption, a topic that is in fact addressed in a large body of literature. What has received little attention, however, is the link between economic conditions and risky health behaviors such as excessive alcohol consumption and smoking. Even among the few studies that do exist (see Ruhm, 1995, 1996; Ettner, 1997; Ruhm, 2005; Dee, 2001; Ruhm and Black, 2002), most conducted in the U.S., conceptual frameworks and data availability vary widely—especially in terms of identification strategy used, evidence for all types of risky health behaviors is mixed, and overall consensus is lacking. For instance, whereas the early studies of Ruhm (1995) and Freeman (1999) offer evidence that alcohol consumption is procyclical and thus decreases during economic recessions, more recent studies using individual-level data find either no effect or evidence of countercyclical alcohol consumption (Dee, 2001; Charles and DeCicca, 2008).

Yet more reliable insights into any potential link between the business cycle and risky health behaviors could be especially useful in timing policy interventions aimed at smoking prevention. The literature to date proposes several channels through which economic conditions may influence risky health behaviors, with the most prominent being the adjustment of wages and hours worked during an economic downturn (see, e.g., Xu, 2013). That is, even conditional on staying employed during a recession, the economic crisis is often accompanied by work-time reductions and wage cuts (or lower bonus payments).

Whereas the former results in increased leisure time, which could lead to an increase in time-consuming positive health behaviors such as physical activity or healthy diets, the decreased income from the latter could have the opposite effect, generating a decrease in any health-related commodities with a positive income elasticity. For less time-consuming negative health behaviors, such as smoking, the income effect might be predominant suggesting a decrease in smoking behavior during a recession. A second channel links economic ups and downs with mental stress, but with no clear a priori picture of the effect's direction (Feldman, 1984). That is, although economic expansion combined with pressure and overtime hours might be stressful, mental stress or fear of becoming unemployed during hard economic times might also be onerous, which could affect the inclination to smoke. There is also ample evidence that aggregate unemployment rates influence perceived job insecurity, which can in turn have a negative effect on health (László et al., 2010). More generally, Clark et al. (2010) show that changes in aggregate economic conditions affect subjective well-being, which may also influence the propensity towards smoking (Chang et al., 2016). Finally, the plight of others may affect cigarette consumption, especially if economic downturns affect relatives and/or friends.

As previously emphasized, the majority of the literature linking macroeconomic conditions and smoking bahavior is from the U.S., with no corresponding European studies that we are aware of, and the marked differences between smoking behaviors in the U.S. and Europe make generalization of the findings problematic. Our main contribution in this paper, therefore, is to analyze the effect of the business cycle on smoking in Germany. To do so, we adopt a reduced-form approach that uses sample selection models to estimate the effect of economic activity, proxied here by regional unemployment, on individual demand for cigarette consumption. We then extend the analysis first to a fixed effects setting in which we also control for sample selection and then to a dynamic context. Finally, we run heterogeneity analyses on men and individuals with a low level of education to check whether these groups are driving our results. We also investigate whether heavy smokers react more strongly to changing economic conditions.

The paper is organized as follows: Section 2 reviews the related literature, section 3 describes the data, and section 4 outlines the methodology. Sections 5 and 6 report the main findings and the results of our robustness checks. Section 7 concludes.

2 Related Literature

Most of the previous literature on the relation between economic fluctuations and smoking behavior identifies a procyclical tendency, meaning that individuals smoke less (more) during an economic downturn (upturn) (see e.g., Ruhm, 2003, 2005). For example, Ruhm (2005), applying a fixed-effects model on data from the U.S. Behavioral Risk Surveillance System (BRFSS), estimates that a one percentage point reduction in the share of employed results in a 0.6 percent drop in the prevalence of smoking. These results imply that the reduction in smoking is mainly driven by the reduced opportunity costs of time-consuming investment in individual health. That is, individuals will devote more time for healthy activities which then in turn will lead to a reduction in nicotine consumption.

Xu (2013), on the other hand, argues that any increase in cigarette consumption during an economic upturn is primarily explainable by income rather than time effects. His analysis is based on data from the BRFSS, the National Health Interview Survey (NHIS), and the Current Population Survey (CPS) with a focus on less educated people. By using an instrumental variable approach to tackle potential endogeneity problems his results point towards wages and hours worked (which are in turn related to economic development) as being drivers of an individual's decision to consume cigarettes. However, he mentions that this effect is mainly driven by the extensive rather than the intensive margin. Given a one-dollar increase in wages his estimates show a higher value for the prevalence in smoking (1.2 percentage points) than for an associated increase in smoking intensity (0.5 percentage points increase for the probability to smoke 10 or more cigarettes).

In fact, there exist several studies which specifically aim on the distinction between the intensive and extensive margins of smoking behavior during an economic shift (see Arcaya et al., 2014 or Falba et al., 2005). For instance, Colman and Dave (2014) identify differing effects of individual's unemployment status on smoking behavior with respect to previous smoking intensity. More specifically, for longitudinal data drawn from the Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth 1979 (NLSY79) their fixed-effects approach show that in case of job loss, the probability towards smoking increases, whereas heavy smokers tend to reduce their cigarette consumption. In addition, these effects seem to differ by gender: while the former effect only shows up for females, the latter appears for both females and males.

Additionally, there are merely few studies providing evidence that smoking decisions seem to vary with the regional unemployment rate, while controlling for individual's employment status. The most related study to ours is Herzfeld et al. (2014). They can show that employed individuals significantly reduce their cigarette intake during a recession. By using the Russian Longitudinal Monitoring Survey (RLMS) and applying a dynamic panel approach, they estimate a statistically significant reduction in the demand for cigarettes given an increase in the regional unemployment rate while being employed. The authors interpret this result as strong evidence for underlying psychological factors, like the fear of job loss, as being the main driver for a reduction of unhealthy behaviors (rather than economic factors like income).

Henkel (2011) also emphasizes the importance of psychological factors by examining 16 articles published between 1990 and 2010. He suggests that higher unemployment rates result in a lower amount of work stress of the affected individuals in a particular region, which in turn leads to a lower cigarette consumption of the population. The positive relationship between work stress and cigarette consumption is also carried out by several other studies (Kouvonen et al., 2005; Radi et al., 2007; Heikkilä et al., 2012).

Overall, although the reasons remain unclear, the effects of regional (aggregate) economic development (proxied by regional unemployment) and individual economic status (proxied by individual employment status) on smoking decisions differ substantially. In fact, the procyclical pattern of smoking decisions with regard to economic fluctuations vanishes when the analysis focuses on individual employment situations rather than economic development as a whole. Arcaya et al. (2014), for instance, drawing on offspring cohort data from the Framingham Heart Study (FHS), predict higher odds ratios of smoking for unemployed individuals by using a logistic panel regression technique. Additionally, they show that not only the extensive, but also the intensive margin of smoking is affected by unemployment, i.e. that smokers are more likely to increase their nicotine consumption after losing their job. Several other studies draw similar conclusions (Hammarström and Janlert, 1994; Falba et al., 2005; Weden et al., 2006; Tekin et al., 2013).

In sum, the relation between the state of the economy and an individual's smoking decisions remain ambiguous. Furthermore, several studies find heterogeneous results conducting subgroup analysis with respect to gender (Hammarström and Janlert, 1994; Herzfeld et al., 2014), income (Ruhm, 2005; Xu, 2013), and/or education (Weden et al., 2006; Tekin et al., 2013). These comparatively huge differences in outcomes could be attributed to several possible reasons: First, some studies suffer from a comparatively short investigation period (linked with a small sample size) which makes it hard to identify a reliable causal relationship. Second, a large body of the literature focuses on particular subgroups of the population only, which makes the generalization of the effect almost impossible. Third, many studies do not address the issue of possible selection adequately, which, in turn, could be a main reason for the mixed evidence found in earlier studies. Finally, in addition to the diversity of findings, nearly all aforementioned studies consider the case of the U.S. To the best of our knowledge, no comparable studies exist for Europe, which exhibits considerably different trends in smoking behavior and general labor market conditions (e.g., labor market rigidity, social insurance).

3 Data and Descriptives

For our analysis, we use 2002-2014 data from the German Socio-Economic Panel (SOEP), a long-running representative panel dataset of rich information on employment, risky behaviors, and health. Information on smoking behavior is available for every second year starting in 2002. We can exploit seven waves (for a 12-year period) that report whether an individual currently self-declares as a smoker and how many cigarettes, pipes, cigarillos, or cigars the respondent smokes a day.[1] In total, out data set contains 142,164 individual observations from 26,886 households, meaning an average of almost 20,300 individual observations per wave.[2]

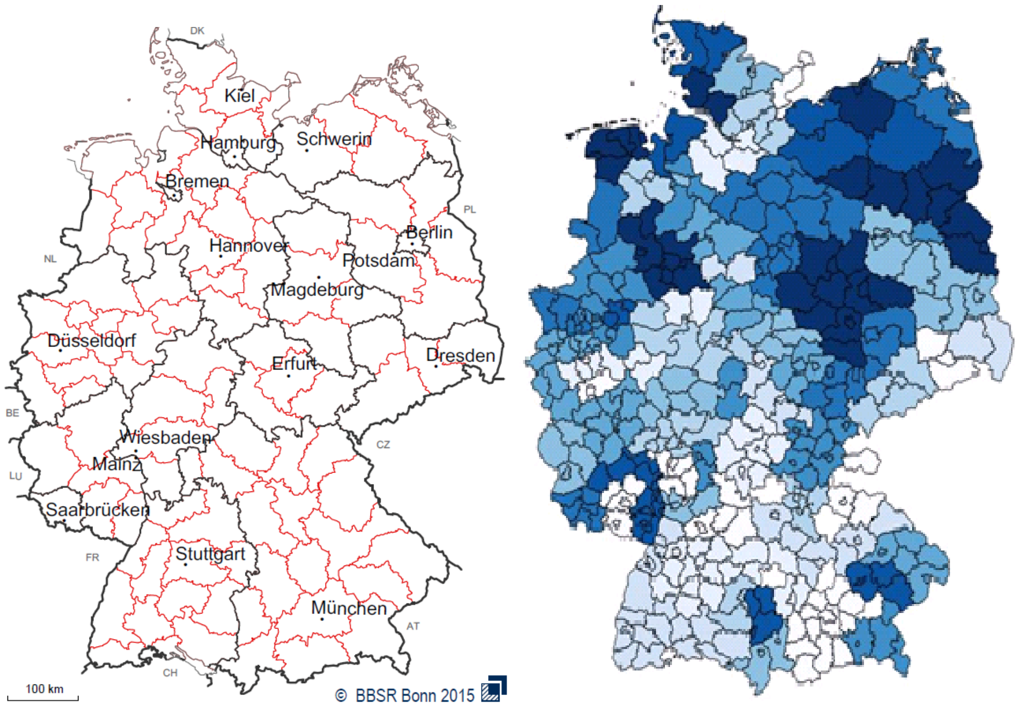
A major advantage of the SOEP is that it contains the respondent's area of residence at the time of the interview—whose value corresponds to official geographic units. The SOEP data can thus be matched with official macro data on the following formal geographic levels: federal states (Bundeslaender), regional policy regions (Raumordnungsregionen, RORs), administrative regions (Regierungsbezirke), counties (Kreise and kreisfreie Staetde), municipalities (Gemeinden), and zip code areas (Postleitzahlengebiete) (Knies and Spiess, 2007). For the purpose of this study, we use the 96 German regional policy regions (see Figure 1) distinguished by the Federal Office for Building and Regional Planning based on commuter traffic and economic linkages (BBSR (Bundesinsitut fuer Bau-, Stadt- und Raumforschung), 2016b). These geographical subunits are defined to capture local economic trends and are thus most suitable for our research question. In our sample, there are a minimum of 18 and a maximum of 1,017 individuals located within these RORs.

Because we are interested in the impact of regional economic activity on individual smoking behavior, we proxy economic activity by the unemployment rate; that is, the percentage of unemployed individuals among the civilian labor force. This variable, measured on ROR geographic level and obtained from the Indicators, Maps, and Graphics on Spatial and Urban

[1] Although the risk of underreporting unhealthy behavior in surveys such as the SOEP is well recognized (Warner, 1978), our main findings will be unaffected if the underreporting is independent of regional economic activity.

[2] Because in some waves, high-income households or individuals with migration backgrounds are oversampled, we appropriately weight our variables whenever possible (Haisken-DeNew and Frick, 2005).

Figure 1: Regional Policy Regions and Regional Shares of Smokers



(a) Regional Policy Regions (b) Regional Shares of Smokers

Note: Subfigure (a) shows a map of Germany divided by 16 federal states (black lines) and 96 regional policy regions (red lines) (BBSR (Bundesinsitut fuer Bau-, Stadt- und Raumforschung), 2016c). Subfigure (b) plots variation in smoking prevalence across German counties.

Monitoring database (Indikatoren und Karten zur Raum- und Stadtentwicklung (INKAR)) of the Federal Office for Building and Regional Planning (BBSR (Bundesinsitut fuer Bau-, Stadt- und Raumforschung), 2016a), exhibits considerable temporal and regional variation. Our timespan, for example, includes major business cycle movements such as the crisis in 2008. Subfigure (b) of Figure 1 illustrates plenty of regional variation in smoking behavior, whereby darker regions indicate a higher share of smokers.

On the individual level, we control for age, age squared, gender, migrant background, marital status, education (no degree, graduation from low, middle, or high secondary school track, university degree), weekly hours worked, and body mass index (BMI). The household characteristics controlled for are net household income and number of children living in the household. We also include a regional indicator for East Germany and the national consumer price index for tobacco products, alcoholic beverages, or food products.

Table 1: Sample Means for Selected Variables

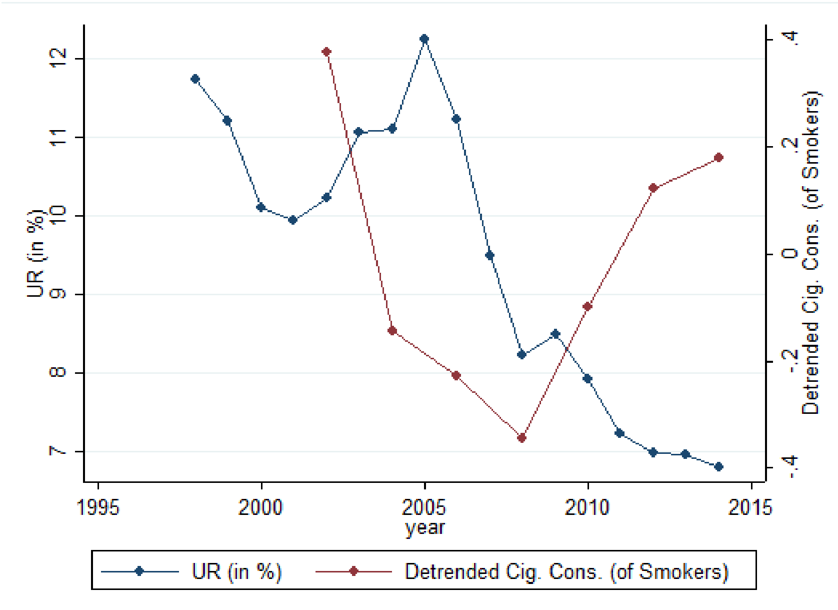
Variable	Weighted Mean (Full Sample)	Weighted Mean (Low-Educated Men)
Outcomes		
Smoker	32.8 %	41.0 %
# of Cigs/Day (of Smokers)	15.4	17.7
Covariates		
Male	48.6 %	100 %
Age	43.6 years	45.3 years
No Degree	2.3 %	3.9 %
Lower educational degree	62.0 %	96.1 %
High School degree	26.4 %	-
Employed	70.3 %	75.0 %
Weekly hours (employed)	37.9 h	43.2 h
Married	54.6 %	56.9 %
Migrant Background	22.4 %	15.9 %
BMI	25.7	26.8
HH Income	37,763 €	35,003 €
# of children in HH	0.5	0.5

Note: The table shows the weighted means of selected variables for the full sample and the subsample of less educated men. The observations are weighted with the SOEP sampling weights. HH income is annual disposable household income.

The means of our outcome and control variables are summarized in Table 1, which shows that one third of all observations are smokers who consume on average 15.4 cigarettes a day. Note that in our empirical analyses, we drop outliers who smoke more than 50 cigarettes per day or have a BMI over 45. We further restrict our sample to the potential working population by excluding individuals younger than 15 years or older than 67 years. Table 1 also shows that 48.6 percent of our full sample is male, and the average age is 43.6 years. A majority (62 percent) has a lower level of education (Hauptschul- or Realschulabschluss), with only 26.4 percent having a (general) higher education entrance qualification. Almost 70.3 percent are employed, and those who are employed work on average 37.9 hours per week. 54.5 percent are married, the average annual after-tax household income is €37,762, and an average household includes 0.5 children.

The sample in the last column of the table is restricted to men without a high school diploma. The share of smokers in this subsample is eight percentage points higher than in the full sample, and less educated male smokers consume on average two cigarettes more per day. Because these individuals might be more affected by economic activity, we take a closer look at this subgroup in a later section.

Figure 2: Unemployment Rate and Cigarette Consumption



Note: The figure shows the average unemployment rate (UR, blue line) and the average, yearly de-trended cigarette consumption of smokers (red line) over the investigation period for whole Germany.

Figure 2 plots the average regional unemployment rate (blue line) against cigarette consumption (red line) for the smoking subpopulation over time. Note that we de-trended the consumption variable here to account for a general and continuous decline in cigarette consumption over time (e.g., due to a declining social acceptance). Graphically, the two variables seem to be negatively correlated except for the survey years 2006 and 2008. One explanation may be delayed adjustments of individual smoking behavior to changes in the unemployment rate. However, note that the graphic is limited since the smoking data is available every second year only.

4 Methodology

We first consider extensive margin responses to changes in regional economic activity. In all specifications, we proxy the business cycle by the regional unemployment rate on ROR level.[3] The conditional probability of being a smoker for individual i in time period t is modelled as

$$\text{smoker}_{it} = \Pr(\text{smoker}_{it} = 1|\boldsymbol{x_{it}}) = F(\boldsymbol{x'_{it}\beta^0}), \tag{1}$$

where $F(\cdot)$ is a parametric function of $\boldsymbol{x'_{it}\beta^0}$ in its most general form.[4] $\boldsymbol{x_{it}}$ is a vector of individual, household and regional covariates. This binary model can be interpreted as a latent variable model based on latent variable y^*.[5] This continuous, but unobservable variable can be written as

$$\begin{align} y^*_{it} &= \beta^0_0 + \boldsymbol{x'_{it}\beta^0} + v_{it} \tag{2} \\ &= \beta^0_0 + \boldsymbol{I'_{it}\beta^0_1} + \boldsymbol{H'_{it}\beta^0_2} + \boldsymbol{E'_{it}\beta^0_3} + \delta^0_r + \tau^0_t + v_{it} \tag{3} \end{align}$$

where $\boldsymbol{I}$ is a vector containing the individual characteristics of age, sex, and weekly work hours, plus dummies for being married, coming from a migrant background, and highest educational level. $\boldsymbol{H}$ is a vector of household characteristics, including household income (in log) and the number of children living within the household, while the vector $\boldsymbol{E}$ subsumes regional unemployment and prices. Further, δ_r is a dummy for the East German region, and τ_t denotes year fixed effects. v_{it} is the idiosyncratic error component. Although we do not observe y^*_{it}, we denote whether an individual is a smoker by

[3]We also use GDP per capita as a proxy, however, this does not change our main results.

[4]Here, the superscript zero distinguishes the coefficients from those of the cigarette consumption equation in a later analysis.

[5]In subsequent discussion, latent variables are designated by an asterisk.

$$smoker_{it} = \begin{cases} 1 & \text{if } y_{it}^{*} > 0 \\ 0 & \text{if } y_{it}^{*} \leq 0. \end{cases} \tag{4}$$

Taking Equation (2) into account, Equation (1) can be rewritten as

$$\begin{aligned} \Pr(smoker_{it} = 1) &= \Pr(\beta_0^0 + \boldsymbol{x'_{it}}\boldsymbol{\beta^0} + v_{it} > 0) &(5)\\ &= \Pr(-v_{it} < \beta_0^0 + \boldsymbol{x'_{it}}\boldsymbol{\beta^0}) &(6)\\ &= F(\boldsymbol{x'_{it}}\boldsymbol{\beta^0}). &(7) \end{aligned}$$

In our main specifications, we use a logit model, which indirectly assumes that the error component v_{it} is logistically distributed. In other words, $F(\cdot)$ is the cumulative distribution function of the standard logistic distribution, and v_{it} is symmetrically distributed around zero.

In a second step, we model the intensive margin of smoking behavior to assess whether, conditional on the individual being a smoker in a given time period t, the number of cigarettes smoked react to the regional business cycle. The cigarette consumption equation is modeled as follows:

$$cons_{it}^{*} = \beta_0^1 + \boldsymbol{I'_{it}}\boldsymbol{\beta_1^1} + \boldsymbol{H'_{it}}\boldsymbol{\beta_2^1} + \boldsymbol{E'_{it}}\boldsymbol{\beta_3^1} + \delta_r^1 + \tau_t^1 + \alpha_i^1 + u_{it}. \tag{8}$$

In this analysis, however, if an individual is a smoker, the number of cigarettes smoked is inherently positive, so if v_{it} of the smoking equation is correlated with u_{it} of the consumption equation, not controlling for sample selection would lead to biased estimates.[6] Such bias is potentially worse in panel settings (Baltagi, 2008). Thus, Equation (1) provides for selection between smokers and nonsmokers by implying the following observability rule:

[6] Because our results section reports some estimates that do not take selection into account, we also present standard fixed effects and Tobit estimates.

$$cons_{it} = cons^*_{it} \;\; \times \;\; \mathrm{I}\{smoker_{it} = 1\}, \tag{9}$$

where I denotes an indicator function which equals one if the condition in brackets (being a smoker) is satisfied. It is important to note that Equation (8) contains the same covariates as Equation (1) with one exception: only the latter includes the educational level (exclusion restriction). In fact, this variable only enters the selection equation because it is plausible to assume that educational level influences the decision to smoke but not the number of cigarettes smoked (at least if we control for income and include individual fixed effects). We thus first estimate a general Heckman sample selection model on the pooled data without taking into account the time dimension and then employ a two-step estimation based on the following conditional expectation:

$$\mathbb{E}(cons_{it}|\boldsymbol{x_{it}}, y^*_{it} > 0) = \beta^1_0 + \boldsymbol{x'_{it}\beta^1} + \sigma_{01}\lambda(\boldsymbol{x'_{it}\beta^0}) \tag{10}$$

$$\text{where } \lambda(\cdot) = \frac{\phi(\cdot)}{\Phi(\cdot)} \tag{11}$$

and σ_{01} is the correlation of the two error terms. The last part of Equation (10) can be estimated by running a probit regression of Equation (1) and predicting $\lambda(\boldsymbol{x'_{it}\hat{\beta}^0})$, the inverse Mills ratio.

We extend the analysis in three ways. First, we exploit the panel dimension for identification by estimating year-by-year probits for the smoking equation, calculating the selection term λ, and then using a within transformation (for smokers only) to account for unobserved heterogeneity. Second, to account for a potential correlation between $\boldsymbol{x^1_{it}}$ and v_{it} in all time periods of the selection equation through unobserved effects, we rerun the probit regressions but include in each period the regressors for all other periods. Finally, to account for addictive behavior, we move to a dynamic context

$$cons_{it} = \beta^1_0 + cons_{it-1} + \boldsymbol{x'_{it}\beta^1} + \lambda(\boldsymbol{x'_{it}\hat{\beta}^0}) + u_{it} \tag{12}$$

in which $cons_{it-1}$ denotes lagged cigarette consumption. We estimate this consumption equation using first the Arellano and Bond (1991) FD GMM-IV estimator and then the Blundell and Bond (1998) system GMM-IV estimator. Whereas the former uses lagged values as instruments for the first-differenced variables, the latter also includes level equations to gain efficiency. This dynamic approach, however, has the drawback that we must condition on being a smoker in the two preceding periods and thereby lose additional observations.

5 Results

Extensive Margin

The estimation results for the extensive decision to smoke are reported in Table 2. Column (1) presents the estimates using a linear probability model (LPM) in which we regress the binary smoker variable on the regional unemployment rate and the set of control variables. Columns (2) and (3) report results of a logistic regression model. In Specification (3), we augment the regression by a full set of year fixed effects and a regional indicator for East Germany. We use cluster-robust standard errors at the ROR level to allow for correlation in the error term of individuals living in the same area.

In all specifications, the coefficient estimate for the regional unemployment rate is positive and highly statistically significant, indicating that an increase in regional unemployment rate leads to an increase in the propensity towards smoking. Since the logit regression coefficients are not directly interpretable in quantitative terms, we additionally calculate (but do not report) the marginal effects at the mean, identifying a marginal effect of 0.0072 for Specification (3). This result implies that a one percentage point increase in the regional unemployment rate is associated with a 0.7 percentage points increase in the propensity towards smoking (evaluated for an average individual). Thus, the magnitude of the effect is as well consistent through all specifications. Evaluated at the overall mean smoking rate of 32.8 percent, this is a relative increase in smoking prevalence of 2 percent.

Note that the coefficients related to the individual employment status are significant and

Table 2: Results for Smokers

	(1) LPM	(2) Logit	(3) Logit
Reg. Unemployment	0.00630***	0.03092***	0.03358***
	(0.00157)	(0.00765)	(0.00880)
Employed	-0.03345**	-0.15961**	-0.16230**
	(0.01473)	(0.07421)	(0.07387)
Hours Worked	0.00069*	0.00344*	0.00348*
	(0.00036)	(0.00182)	(0.00181)
Male	0.08555***	0.40751***	0.40718***
	(0.00789)	(0.03937)	(0.03937)
Migrant Background	-0.00309	-0.01391	-0.01428
	(0.01082)	(0.05200)	(0.05199)
Married	-0.09624***	-0.45163***	-0.45138***
	(0.00959)	(0.04518)	(0.04532)
BMI	-0.00671***	-0.03275***	-0.03280***
	(0.00083)	(0.00415)	(0.00418)
# of Children in HH	-0.00353	-0.01612	-0.01613
	(0.00507)	(0.02446)	(0.02446)
HH Income (in log)	-0.07071***	-0.34269***	-0.34276***
	(0.00583)	(0.02850)	(0.02858)
Year FE	-	-	X
Observations	106,797	106,797	106,797

Note: The table shows the results for the smoking equation. The dependent variable is binary and equal to one if the individual smokes a positive number of either cigarettes, pipes, cigarillos, or cigars a day; zero otherwise. Regional unemployment is measured in percentage points. Cluster-robust standard errors in parentheses, clustered on ROR level. All specifications include educational level, price controls, and a dummy for East Germany. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

negative, meaning that the own employment status has an opposing influence on the likelihood of being a smoker. On the other hand, the coefficients of hours worked per week are positive and marginally significant through all specifications, indicating that individuals who work more hours per week are more likely to smoke. One possible explanation is that individuals who often work in the evening or at the weekend may be more susceptible to stress. Men and unmarried individuals are also more prone to smoking, although the probability of being a smoker declines with higher educational levels (not shown in the table) and decreases with BMI. Household income also has a highly significant negative influence on being a smoker, but the number of children living in the household seems to have no impact on smoking prevalence.

Intensive Margin

Tables 3 and 4 report the results for the intensive margin. In Table 3, we estimate a standard OLS model for Specification (1) and a Tobit (censored regression) model for Specification (2). Thereby, we do not consider any selection mechanisms, but restrict the sample to smokers. Consequently, the sample size reduces to approximately one third.

All specifications include year fixed effects and a regional indicator for East Germany. We use the logarithm of cigarette consumption as dependent variable for comparability with later results.[7] In both analyses, the coefficient of interest is initially positive and significant, but once we control for individual heterogeneity, as with the within-group fixed effects estimator (WG-FE) in Specification (3), the sign turns negative. In quantitative terms, a one percentage point increase in the regional unemployment rate leads to a 0.5 percent decrease in cigarettes smoked. Since an average smoker consumes approximately 15.4 cigarettes per day, this corresponds to a reduction of almost 0.1 cigarettes per day.

Next, because the estimates presented so far could be biased by sample selection, Table 4 reports static models, Specifications (1)-(3), and a dynamic model, Specification (4), that consider this potential endogeneity. For Specification (1), which estimates the two-step Heckman model, we again find that economic activity has a negative effect on cigarette consumption, although the magnitudes are somewhat smaller. Nevertheless, given the rejection of the null hypothesis of no correlation between error components, sample selection seems to matter. Moreover, the t-statistic associated with the inverse Mills ratio strongly suggests sample se-

[7] Using levels yields no differences in sign or significance.

Table 3: Results for Cigarette Consumption (Smokers only)

	(1) OLS	(2) Tobit	(3) WG-FE
Reg. Unemployment	0.00840*	0.00519***	-0.00515**
	(0.00435)	(0.00130)	(0.00226)
Hours Worked	0.00002	0.00024	0.00125***
	(0.00035)	(0.00017)	(0.00016)
Cluster Level	ROR	-	ROR
Observations	34,834	38,588	38,849

Note: The table shows results for cigarette consumption. Robust, and if possible, clustered, standard error are in parentheses. The dependent variable is the logarithm of smoked cigarettes, pipes, cigarillos, and cigars. All specifications include individual and household controls, as well as year fixed effects. The sample is restricted to smokers. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

lection by giving evidence of a joint probability distribution with negative covariance between u_{it} and v_{it}. Nonetheless, because this model does not account for individual time-invariant unobserved heterogeneity, the Specification (1) estimates may still be biased.

Specifications (2) and (3) both include individual fixed effects, and their estimates differ only in the computation of the inverse Mills ratio. From Specification (3) onward, this ratio is computed using the reduced form probit in each year with the covariates of all other years included (Mills2). Both estimates have the same negative sign and are considerable larger in absolute terms than those for Specification (1). The sign for hours worked becomes positive as soon as we include individual fixed effects; however, the Mills ratio, although statistically significant in Specifications (1) and (3)—which provides evidence for sample selection—is no longer significant in Specification (2).

Column (4) reports the estimates for the dynamic model, which introduces persistence into the consumption equation by including the lag of the dependent variable. The results confirm the earlier findings. The coefficient of interest is negative and highly significant, and the coefficient of the lagged dependent variable has the expected positive sign, indicating addictive behavior. In this efficient system estimator, sample selection seems to be substantial. For the

Table 4: Results for Cigarette Consumption (Sample Selection Correction)

	(1) Heckman	(2) WG-FE I	(3) WG-FE II	(4) System
Reg. Unemployment	-0.00140	-0.00722**	-0.00792**	-0.00514***
	(0.00153)	(0.00354)	(0.00372)	(0.00161)
Hours Worked	-0.00152***	0.00071*	0.00094***	0.00006
	(0.00021)	(0.00038)	(0.00031)	(0.00024)
Lagged ln cig.cons.				0.22310***
				(0.02206)
Mills	-0.63097***	-0.13524		
	(0.02535)	(0.09620)		
Mills2			-0.10006***	-0.16178***
			(0.03907)	(0.02546)
AR(1)				0.000
AR(2)				0.087
Sargan Test				0.264
Hansen Test				0.319
Cluster Level	-	ROR	ROR	-
Observations	118,453	33,564	34,831	13,097

Note: The table shows the results for cigarette consumption while controlling for sample selection. Robust, and if possible, clustered, standard errors are in parentheses. The dependent variable is the logarithm of smoked cigarettes, pipes, cigarillos, and cigars. In Specification (1), we estimate a two-step Heckman model that includes educational levels in the selection equation. In Specifications (2) and (3), we estimate a within-group fixed effects model that includes the selection term. In Specification (4), we apply the Blundell-Bond system estimator and instrument the first difference of the first lag of log cigarette consumption with the second and all further lags of the level of log cigarette consumption. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

dynamic model, we also assess validity using standard specification tests. That is, we report the p-values of the Arellano-Bond tests for AR(1) and AR(2) in first differences. It tests the null hypothesis that the level errors are not autocorrelated of an order 1 and 2 respectively. The results reveal that, as expected, we have to deal with first order autocorrelation since the p-value of the AR(1) test is 0.000. However, the p-value for the AR(2) test is 0.087, so we cannot reject no autocorrelation of order 2 at a 5 percent level of significance. We then show that the p-values of the Sargan test and the more robust Hansen test of overidentifying restrictions support the estimates for the Blundell-Bond estimator. In both cases, the null hypothesis can clearly not be rejected, meaning that our instrumenting procedure works well. The fact that the results change only marginally between specifications further indicates the robustness of the effect of interest.

All in all, the results indicate that the propensity towards smoking increases in economic hard times. However, conditional on being a smoker, the actual number of smoked cigarettes decreases by around 0.5-0.8 percent for an one percentage point increase in the regional unemployment rate. Bearing in mind that Germany exhibits variation in regional unemployment rates of more than 20 percentage points over regions and time, the effects can be interpreted more meaningfully for an, e.g., 10 percentage point increase in the economic proxy. Then, a 5-8 percent decrease in smoking intensity translates into a reduction of about 1 cigarette per day.

6 Heterogeneity Analyses

Analysis by sex and educational level

Because women and less educated individuals are often more affected by economic slumps, we split our sample based on gender and educational level to determine whether these groups are driving our results (see Table 5). Here, rather than interacting regional unemployment with a corresponding group dummy, we split the sample by sex (males in Column (1); females in Column (2)), which, although it reduces the sample size, allows comparison of the different effects of the other covariates.

When considering the significance of the results, note that we lose even more observations in the analysis of individuals with low education.[8] Table 5 focusses on our preferred specifications, namely the logit regression with year fixed effects (Specification (3) of Table 2) for the extensive margin (*Smoker*) and the dynamic System estimator (Specification (4) of Table 4)

[8] If we further condition on being a smoker in the dynamic model, we are left with fewer than 4,000 observations.

Table 5: Results for Cigarette Consumption by Sex and Education

	(1) Men	(2) Women	(3) Low	(4) High
Smoker				
Reg. Unemployment	0.0276***	0.0418***	0.0309**	0.0588***
	(0.0104)	(0.0117)	(0.0121)	(0.0135)
Cigarette Consumption				
Reg. Unemployment	-0.00274	-0.00755***	-0.00558***	-0.000951
	(0.00217)	(0.00239)	(0.00193)	(0.00388)

Note: The table shows the coefficient and corresponding standard errors of the regional unemployment variable. It reports the results of a logit regression with year fixed effects for the extensive margin (*Smoker*) and of the dynamic System estimator for the intensive margin (*Cigarette Consumption*). Low education means no degree or a certificate from the two lowest school tracks (Hauptschule or Realschule); high education means a high school diploma ((Fach-)Hochschulreife). *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

for the intensive margin (*Cigarette Consumption*). Further, we report only the coefficients and corresponding standard errors (in brackets) of the regional unemployment variable for all outcomes. These estimations reveal no large differences in the smoking decision with only slightly larger effects for women and highly educated individuals. On the contrary, the overall effect for the intensive margin seems to be driven by women and less educated individuals: the coefficients are highly significant and much larger in absolute terms than for the other two subgroups. The findings imply that women and less educated individuals are most likely to reduce their cigarette consumption in hard times, with a one percentage point increase in the regional unemployment rate reducing the number of cigarettes smoked by 0.6 to 0.8 percent.

Analysis by smoking intensity

In a subsequent step, we use the sensitivity analysis proposed by Ruhm (2005) to assess whether individuals with extreme health behaviors respond more strongly to changing regional conditions. In particular, we focus on heavy versus occasional smokers, defined as the top and bottom 10 percent of the cigarette consumption distribution. Our measure is a dummy variable equal to one if an individual smokes more than 25 (less than 5) cigarettes per day, a value that represents the 90th (10th) percentile. We test for significant differences by interacting

Table 6: Results for Cigarette Consumption by Smoker Type

	(1) Heavy Smokers	(2) Occasional Smokers
Heckman		
Reg. Unemployment	-0.00239*	0.00007
	(0.00142)	(0.00091)
Interaction	-0.00235	0.00993***
	(0.00281)	(0.00134)
System		
Reg. Unemployment	-0.00384**	-0.00427***
	(0.00152)	(0.00131)
Interaction	-0.00208	0.00369
	(0.00199)	(0.00316)
Individual Controls	X	X
Household Controls	X	X
Year FE	X	X

Note: The table shows the results for cigarette consumption by heavy and occasional smokers (top and bottom 10 percent of cigarette consumption distribution). Robust standard errors are in parentheses. We report only the coefficients of the regional unemployment rate and their interactions with the smoker type dummy. The specifications remain identical to those in the main analysis. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

this dummy with the regional unemployment rate.

Table 6 lists the results for the Heckman and the dynamic System estimator. We report only the regional unemployment estimate and its interaction with the smoker type dummy. For heavy smokers, the interaction term is negative, albeit not significant in both specifications. However, the fact that the total effects are always more pronounced and significant for those at the higher end of the cigarette consumption distribution suggests that, as reported by Ruhm (2005), these individuals tend to react more strongly to economic changes. Thus, the effect of an increase in regional unemployment is amplified, meaning a more negative outcome for heavy smokers. For occasional smokers, in contrast, we find a positive interaction coefficient. Adding together the positive effect of the interaction term and the negative effect of the regional unemployment rate results in an overall positive effect for the Heckman specification.

These outcomes suggest that occasional smokers increase their cigarette consumption during hard economic times.

7 Conclusion

Despite a broad body of literature on the determinants of smoking, relatively little research examines how the macro economy affects the inclination to smoke, especially in a European context. Yet, as the primarily American literature shows, the state of the macro economy appears to influence all types of risky behaviors and smoking in particular. In fact, most U.S. studies provide evidence that when economic conditions weaken heavy drinking and drunk driving, smoking, obesity, and physical inactivity decrease while diets improve (Gruber and Frakes, 2006; Cawley and Ruhm, 2011). Given the different smoking prevalences and cultures in European countries (and especially Germany), the American study results cannot be validly generalized to Europe. In this paper, therefore, we seek to fill this research gap by analyzing German Socio-Economic Panel data combined with macroeconomic variables on the regional (ROR) level.

By applying dynamic sample selection models to these panel data, we identify a significant increase in the probability that an individual will start to smoke when unemployment rates increase, a result that differs from many of the U.S. findings. Conversely, however, conditional on the individual being a smoker, the number of cigarettes smoked per day decreases in bad times, especially among less educated individuals and women. As might be expected, however, these effects are not large: for an average individual, a one percentage point increase in the unemployment rate increases the propensity to become a smoker by 0.7 percentage points. Conversely, a one percentage point increase in the regional unemployment rate leads to a 0.5-0.8 percent decrease in cigarettes smoked. Thus, for an average smoker, a 10 percentage points surge in the unemployment rate reduces the number of cigarettes smoked by about one per day.

Our investigation also shows that when analyzing cigarette consumption across the business cycle, researchers must take sample selection issues into account. For example, were we not to correct for selection bias, our results would show a pronounced procyclical relation between smoking intensity and unemployment rates. Yet in the extant literature, such precautions are seldom observed.

In fact, our analysis does reveal a small business cycle effect on smoking, one that is only partially comparable to those identified for the United States. That is, as in the U.S., smoking among smokers is countercyclical, but a recession can increase the inclination to become a smoker. What remains speculative is the mechanism underlying these dynamics. Why, for example, does the probability of becoming a smoker increase in a recession while smokers themselves tend to smoke less? Answering this question is problematic because the possible mechanisms are so numerous. One the one hand, research based on the SOEP shows that increases in aggregate unemployment rates can negatively influence individual well-being, which in turn could influence the probability of an individual's starting to smoke. On the other hand, an economic boom may give rise to long work hours, which could affect workplace stress levels, causing cigarette consumption to show procyclical behavior. Revealing the true nature of these mechanisms requires more detailed information on the motives for smoking, which presents an interesting avenue for future research.

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