ISIGrowth
INNOVATION-FUELLED, SUSTAINABLE, INCLUSIVE GROWTH

Working Paper

Innovation, demand and growth

Alessio Moneta
Scuola Superiore Sant'Anna, Institute of Economics, Pisa, Italy

Elena Stepanova
Scuola Superiore Sant'Anna, Institute of Economics, Pisa, Italy

22/2018 May

This project has received funding from the European Union Horizon 2020 Research and Innovation action under grant agreement No 649186

INNOVATION, DEMAND AND GROWTH

Alessio MONETA[1] Elena STEPANOVA[2]

ISIGrowth DD 6.1

The attached paper, titled "Changes in consumption patterns and innovation: an empirical analysis" was written with the aim of addressing the empirical part of the Task 6.1 of ISIGrowth, which is devoted to study the interactions between innovation, demand generation and aggregate growth. The general goal of Task 6.1 is to investigate the conditions under which higher rates of innovation lead to more sustained economic growth by stimulating aggregate demand instead of yielding labour displacement and income inequality. In particular, the deliverable 6.1 was designed to investigate the link among innovation, changes in marginal propensities to consume and inequality using data-driven methods. This allows us to understand whether changes in demand patterns may, in turn, hinder economic growth via income redistribution against households with higher marginal propensities to consume.

Thus in the attached paper we employ panel vector-autoregressive models to analyse the dynamic interdependencies among (i) innovation activity as measured by patent applications across sectors, (ii) households marginal propensity to consume across expenditure categories, as measured by Engel curves derivatives and (iii) inequality in expenditure patterns across income. We have used British data on household expenditures, from U.K. Family Expenditure Survey and the Expenditure and Food Survey data, as well as Amadeus data on patent applications. The original idea was to use Eurostat data, i.e. Community Innovation Surveys (CISs) and the European Community Household Panel (ECHP). Unfortunately, econometric analysis through vector-autoregressive models is only possible on availability of annual data for relatively long time-periods, that is why we were not able to use CIS surveys data on innovations, which are available only for 7 years. Moreover, ECHP data did not permit us to estimate Engel curves, which we realized to be the most reliable way to estimate marginal propensities to consume. Thus we used on British household budget data, which relied on surveys conducted between 1968 and 2013. In future, we plan to extend our analysis using household budget data and patent applications from other European countries (Germany and Italy in particular), depending on data availability.

[1]Scuola Superiore Sant'Anna, Institute of Economics, Piazza Martiri della Libertà 33, 56127 Pisa, Italy. Email: *amoneta@sssup.it*

[2]Scuola Superiore Sant'Anna, Institute of Economics, Piazza Martiri della Libertà 33, 56127 Pisa, Italy. Email: *e.stepanova@sssup.it*

CHANGES IN CONSUMPTION PATTERNS AND INNOVATION: AN EMPIRICAL ANALYSIS

Alessio MONETA[1] Elena STEPANOVA[2]

July 18, 2016

Abstract

Using UK households expenditure data and Amadeus data on patent applications, we empirically analyze the interaction between changes in consumption patterns and innovation activity. Consumption patterns are measured through real Engel curves that are cross sectionally estimated from 1968 to 2013. The interaction mechanism between shifts in real Engel curves and innovation activity is identified and measured through a structural vector autoregression analysis that allows discriminating between the contemporaneous and the lagged effect. We also examine the role played by changes in relative prices and changes in income inequality. We find, for specific sectors, significant causal effects between demand and innovation, suggesting that an increase of interest in a particular good by consumers brings about a positive response by firms in the form of increase of inventive activity.

Keywords: Engel curves, Demand-pull innovation, Demand saturation, Inequality, Marginal propensity to consume, Causality, Structural Vector Autoregressions.

JEL classification: C14, C22, D12, O33.

---

[1]Scuola Superiore Sant'Anna, Institute of Economics, Piazza Martiri della Libertà 33, 56127 Pisa, Italy. Email: *amoneta@sssup.it*

[2]Scuola Superiore Sant'Anna, Institute of Economics, Piazza Martiri della Libertà 33, 56127 Pisa, Italy. Email: *e.stepanova@sssup.it*

We thank Andreas Chai, Tommaso Ciarli, Valeria Cirillo, Giovanni Dosi, Dario Guarascio, Arianna Martinelli, Daniele Moschella, Maria Savona and Mario Pianta for their suggestions. We are also grateful to the U.K. Central Statistical Office for making available the U.K. Family Expenditure Survey and the Expenditure and Food Survey data through the Economic and Social Data Service. We acknowledge funding from the European Union Horizon 2020 research and innovation programme under grant agreement No. 649186 (ISIGrowth, Task 6.1).

1 Introduction

We study the casual relationship between households consumption patterns, as described by Engel curves, and firms innovative activity, as proxied by patents applications.[1] The question about the casual direction between consumption and innovation is not settled and, to our knowledge, there are no empirical studies that looked at this question linking household budget to patent data. This paper contributes to the old and well-known literature debate on *demand pull* vs *technology push* innovative activity (for the survey see Stoneman, 1979).

From one theoretical perspective, an increase in consumption increases profits and stimulates innovative activity. This account is known as *demand pull* innovation, as coined by Schmookler (1966) (cfr. also Scherer, 1982). Schmookler's main idea was that demand played a leading role in determining both the direction and magnitude of innovation. Strong demand has positive impact on patenting because it increases returns to inventive activity. The *demand pull* perspective and the literature on structural change (Pasinetti, 1981) emphasize the positive effect that a strong demand dynamics has on the development and diffusion of new products. But *demand pull* direction of causality between innovation and demand proposed by Schmookler was questioned several times. The opposite direction of causality is an equally plausible hypothesis. It later came to be called the *technology push* hypothesis, see Rosenberg (1976), Dosi (1988). It argues that innovative activity itself increases demand because of the accelerator effects associated with decreasing prices due to process innovation and/or increasing market share due to product innovation. In terms of final households consumption, innovation increases the number of consumption varieties and subsequently increases consumer's interest towards a specific category of consumption. Bils and Klenow (2001) found that the introduction of new varieties within a specific category of consumption tends to shift expenditure away from less innovative categories and towards those that feature a high rate of innovation. For example, the introduction of cable television in 1980 has fuelled expenditure on television sets. *Demand pull* and *technology push* effects might be considered as complementary rather than mutually exclusive. In particular, Kleinknecht and Verspagen (1990), using cross section data, show the existence of a mutual dependence between demand and innovation for Dutch manufacturing sectors.

The main limitation of the previous studies is their lack of a substantially long time dimension in the datasets used and so their inability to put forward dynamic models. We show that the time dimension is important in determining a direction of causality. Time-series format of our data allows us to study co-movements between time-series using structural vector autoregression (SVAR) approach, which is an advantage with respect to standard cross-sectional analysis.[2]

In contrast with previous studies that proxy demand with investment or industry out-

[1] On the limitations, but also the relevance of the use of patents as a proxy for innovation, see the critical review by Griliches (1990).

[2] Time-series analysis is only possible on availability of annual data for relatively long time-periods, that is why we were not able to use CIS surveys data on innovations, which are available only for 7 years (CIS surveys are advocated to be a better proxy of innovation activity in the industry sector than patent data).

put, we focus on a specific component of demand, i.e. on final households consumption.[3] Von Hippel (Von Hippel, 1986, 2005) outlines the role of the final consumer for innovative activity. We describe households consumption using Engel curves (ECs) that link household expenditure patterns and household income (Engel, 1857). ECs are an essential tool if we want to take into account changes in household income distribution when looking at inter-temporal causal relation of households consumption and firms innovative activity. Important finding of the previous empirical literature on ECs is that ECs shift over time and change their shapes (Moneta and Chai, 2014; Chai and Moneta, 2012). Specifically, EC saturation level (upper limit of households consumption of any particular good) [4] moves over time. Same studies showed that this tendency is associated with changes in the income distribution of households as well as price trends. In the present paper we look whether shifts of ECs over time or/and changes of marginal propensity to consume (measured by EC derivatives) are influenced by or/and influence innovation activity. In doing this, we control for changes in the income distribution, using Gini coefficient, and price trends, using relative prices.

Results of our analysis support the *demand pull* side of the debate on the impact of demand on innovative activity. We find that changes in consumption patterns have positive contemporaneous effect on the innovative activity in the corresponding manufacturing/service sector. We find the existence of positive and significant causal relationship between changes in Engel curves for some good/service and patent applications by the firms that produce this good/service. Specifically, an increase in the average marginal propensity to consume, which we interpret as an increase of interest in a particular good, causes positive responses by firms-producers in the form of increase of inventive activity.

This paper is structured as follows. In the next section we describe the data. Section 3 explains non-parametric method used to estimate the ECs and provides the setup of the SVAR model. Section 4 provides the results of the SVAR analysis. Section 5 concludes.

2 Data

In order to investigate the existence of a causal relationship between consumption and innovation we rely on microeconomic data. We use long historical data on households consumption and firms patents applications in a specific country[5] and in a specific industry sector. We focus on sectors that are largely oriented towards domestic markets and home consumers. We selected only those industry sectors in which more than 50 % of output is consumed domestically (according to OECD countries input-output tables). We study whether in these sectors domestic consumption plays a role in pushing inno-

[3] A number of studies looked at the relation between EU firms exports, as a component of demand, and firms innovative activity ("learning by exporting" hypothesis, see Crespi et al. 2008). The role of demand in the form of households consumption for the EU countries was not yet fully appreciated in the empirical economic literature.

[4] Once EC saturation level is reached, household expenditure will cease to rise in response to increasing income.

[5] For the moment we use UK data but the study will be repeated for other European countries, e.g. Germany and Italy.

vative activity. We pay special attention to service sectors. Cainelli et al. (2006) show the endogenous nature of innovation in services, outlining that innovation act as a self-reinforcing mechanism, which further boosts economic performance. As 75 % of UK GDP comes from service sectors and not industrial production, the interaction between consumption and innovation in services is an important research question. A specificity of services is the fact that they are produced and consumed locally[6]. So our assumption is that domestic consumption should catalyse innovative activity in these sectors. For our analysis we selected only services where patent activity is high, specifically ICT sector.[7]

Households consumption data are taken from the UK Family Expenditure Survey (FES) conducted between 1968 and 2013. From 2001 the FES was actually replaced by a new combined survey, the Expenditure and Food Survey. Goods include food, tobacco and alcohol, foot-and-clothes-wear. Services include transportation (air, water, rail, bus) and two ICT services - telephone and TV. We deflate expenditure in each of the major categories using the category-specific Retail Price Index (RPI). Total expenditure is deflated using the general RPI (the base year used is 1987).

Figure 1 shows how the ECs for the main expenditure categories have evolved over time (in the next section of the paper we explain non-parametric techniques used in the estimation of ECs). Moneta and Chai (2014) andChai and Moneta (2012) have shown the dependency of ECs movements on the changes in the income distribution of households and on the changes in prices. That is why we control for these effects using Gini coefficient and relative prices. Gini coefficient is a measure of statistical dispersion of income distribution in the population. Relative price for a particular consumption category is calculated as a ratio of category-specific RPI over general RPI.

The number of patent applications is taken from the Amadeus database, a commercial database provided by Bureau van Dijk. The database covers all applications made in a given year by firms registered in the UK. For these firms, AMADEUS provides some basic information on patents and production activity. Precisely, we are interested in the year a firm applied for a patent and firm's NACE code (statistical classification of economic activities in the European Community). As Kleinknecht and Verspagen (1990) rightly underlined, there is generally a lag between innovation and final patenting. That is why we use patent applications instead of granted patents to avoid sufficient time lag between innovation (at least in the view of a firm-applicant) and official grant of a patent. Major innovations that happened during the period under consideration include:
1) in the transportation sector: navigation and location systems, automated traffic control systems, automation of booking and ticket sales, automation of passengers control were introduced;
2) in television programming and broadcasting: the growth of cable TV, video recorders displacing 'live' cinema and theater, extension of local TV and radio transmissions;
3) in the food and beverages manufacturing industry: ready-meals, easy-to-handle and time-saving meals, development of new varieties such as diet foot, biological and well-being products;

[6]However ICT technologies recently allows to break this rule

[7]In general, patents are not an adequate proxy of innovation activity in services. The only exception are highly technological service sectors (Licht et al., 1999).

4) in the clothing and footwear industry: the usage of new materials to bring new qualities to old products (such as, for example, elasticity) or/and to diminish production costs. Table 1 below provides matching between firms economic activities and households consumption expenditures. Figure 2 displays time-series of patents applications for a particular industry sector and changes of average marginal propensity to consume for the corresponding consumption category.

Table 1: Industry sector vs household expenditure categories matching table

Firms Economic Activities NACE code	Households consumption expenditure categories
Industry sector	
C 10 - Manufacture of food products	Food expenditure
C 11 - Manufacture of beverages	Alcohol drinks
C 12 - Manufacture of tobacco products	Tobacco
C 14 - Manufacture of wearing apparel C 15 - Manufacture of leather and related products	Clothes and footwear
Service sector	
H 491 - Passenger rail transport, interurban, H 493 - Other passenger land transport, H 501 - Sea and coastal passenger water transport, H 503 - Inland passenger water transport, H 511 - Passenger air transport	Transport expenditure (excluding cars)
J 61 - Telecommunications	Telephone payments (mobile phone is included in the survey from 1996)
J 602 - Television programming and broadcasting activities	Payments for TV—cable—satellite—VCR (satellite TV is included in the survey from 1988)

3 Econometric method

3.1 Engel curves

Consumption patterns are measured, for each time period and for each category of expenditure, by Engel curves. An Engel curve can be written in the following way:

$$Exp_i^j = m_j(x_i) + \varepsilon_i, \tag{1}$$

where Exp_i^j denotes the expenditure of household i on category j, x_i is total expenditure (proxy for income) allocated by household i , $m_j(x) = E(Exp_i^j|x_i)$ and ε_i is the (household specific) error term such that $E(\varepsilon_i|x_i) = 0$. Equation (1) can then be estimated using a cross section of household data by linear or nonlinear least squares, depending on the functional form assumed for $m_j(x)$. However, imposing a functional form would heavily condition our results. Therefore it is preferable to use a nonparametric approach (i.e. a kernel regression) that let $m_j(x)$ to be determined by the data. In our empirical analysis, equation (1) is estimated using the local linear kernel regression proposed by Fan and

Gijbels (1992) and Fan (1993). The estimator is defined as $\hat{m}_j(x_i)$, such that

$$\hat{m}_j(x_i) = \arg\min_{\gamma} \sum_{k=1}^{N} \left[Exp_k^j - \gamma - \delta(x_k - x_i)\right]^2 \mathrm{K}_{b_N}(x_k - x_i), \tag{2}$$

where $\mathrm{K}_{b_N}(\cdot)$ is a suitable kernel function depending on a bandwidth b_N, N is the total number of households present in the sample, and γ and δ are parameters for which the sum on the right hand side is minimized. In comparison with other kernel estimators, e.g. the Nadaraya–Watson and the Gasser–Müller estimator (cfr. Nadaraya, 1964; Watson, 1964; Gasser and Müller, 1979), the local linear estimator (2) has the advantage of having a relatively small bias for finite samples, of being asymptotically efficient, and of displaying better behavior at the extremes of the sample. (For a comparison see Fan and Gijbels, 2003). The choice of the bandwidth can be based on different methods. In our empirical analysis we choose the bandwidth on the basis of the minimization of a polynomial approximation of the mean integrated square error (of $\hat{m}_j(x_i)$), following the approach proposed by Fan and Gijbels (2003).

3.2 Structural VAR and causality

We analyze the causal relationships between shifts in Engel curves and patent applications, using structural vector autoregressive (SVAR) models with identification procedure proposed by Moneta et al. (2013).

In the baseline model we let Y_{gt} be a vector of time series variables:

$$Y_{gt} = \begin{pmatrix} EC_{gt} \\ PA_{gt} \\ RP_{gt} \end{pmatrix},$$

where EC_{gt} is the average cross-section estimation of the real Engel curve for a particular category of expenditure g, PA_{gt} is the number of patent applications corresponding to g, RP_{gt} is a control variable for relative prices, i.e. $RP_{gt} = \frac{p_{gt}}{\bar{p}_t}$, where p_{gt} is the price index for the category g and $\bar{p}_t$ is the price index for the entire basket of goods.

Our method consists of three steps. First we estimate the reduced-form VAR model:

$$Y_{gt} = A_1 Y_{g(t-1)} + \ldots + A_p Y_{g(t-p)} + u_{gt}, \tag{3}$$

where $A_1, \ldots, A_p$ are $k \times k$ (k is the number of entries of Y, i.e. 3 in the baseline model) matrices and u_{gt} is a vector of errors of length k. Second, under the assumption that the data are generated by independent and non-Gaussian shocks, i.e.

$$u_{gt} = P\varepsilon_{gt} \tag{4}$$

we estimate the matrix P through independent component analysis. Third, by applying the LiNGAM algorithm (for details see Shimizu et al., 2006; Moneta et al., 2013), we identify the structural VAR model:

$$\Gamma_0 Y_{gt} = \Gamma_1 Y_{g(t-1)} + \ldots + \Gamma_p Y_{g(t-p)} + \varepsilon_{gt}. \tag{5}$$

The entries of the matrix $B = I - \Gamma_0$ denote contemporaneous causal effects. (Notice that $\Gamma_0 u_t = \varepsilon_t$). The entries of the matrices $\Gamma_1, \ldots, \Gamma_p$ denote lagged effects.

We also estimate two alternative models: a model with EC derivatives, and a model with an inequality index. In the model with EC derivatives we let Y_{gt} be:

$$Y_{gt} = \begin{pmatrix} DEC_{gt} \\ PA_{gt} \\ RP_{gt} \end{pmatrix},$$

where DEC_{gt} is the average cross-section estimation of the derivative of the real Engel curve for a particular category of expenditure g. Thus, the only difference with the baseline model is that we use EC derivatives instead of simple ECs. The EC derivative of a particular good captures the marginal propensity to consume of that particular good. Since declining marginal propensities to consume are usually associated to slowdowns or satiatibility of consumption (cfr. Bruns and Moneta, 2016), the analysis of the relationship between EC derivative and innovative activity shed some light on the link between saturation of demand and innovation.

In the model with inequality index we let Y_{gt} be:

$$Y_{gt} = \begin{pmatrix} EC_{gt} \\ PA_{gt} \\ INEQ_{gt} \end{pmatrix},$$

where $INEQ_{gt}$ is the Gini coefficient, measuring inequality in the population of consumers at time t with respect of expenditures on the good g. The idea here is not only to control for changes in income distribution, but also to analyse whether innovation has some significant impact on expenditure inequality.

4 Results

4.1 Baseline model

In this subsection we show the results for the SVAR analysis with the baseline model (setting the number of lags p equal to one), using UK data from 1968 to 2013 for seven categories of goods and services: 1. food, 2. clothing and footwear, 3. fares and other travel services, 4. alcohol, 5. tobacco, 6. television (products and services), 7. telecommunication.

Table 2 displays the results of the estimate when we pool together the 7 categories of expenditure. Augmented Dickey-Fuller unit root tests suggest the presence of a unit root for some categories (2,3,4,6,7). Therefore we also estimate the SVAR model in first differences. Table 3 shows the estimates of the SVAR coefficients for this case. We also show the results when the same study is performed separately for specific sets of categories of expenditure (see tables 4, 5, 6, 7). When the unit root test is suggesting the presence of a unit root, we take data in first differences, whereas when the hypothesis of unit root is rejected we take the data in levels. We do not find significant effects between innovation activity and changes in EC position. The only significant effects that we find is from relative prices both to shifts of ECs and patent applications. In both cases the effect is negative.

Table 2: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, baseline model (in levels), one lag. Standard errors are reported in the rows named "s.e.". Bold numbers refer to coefficients that are significant at 0.05 level.

	EC_t	PA_t	RP_t	EC_{t-1}	PA_{t-1}	RP_{t-1}
EC_t	0.000	0	**-9.605**	**0.992**	0.000	**9.644**
s.e.	0.000	0	1.569	0.004	0.000	1.625
PA_t	3.385	0	**-123.309**	-3.354	**0.991**	**124.342**
s.e.	1.979	0	56.050	1.989	0.034	57.907
RP_t	0.000	0	0.000	0.000	0.000	**1.020**
s.e.	0.000	0	0.000	0.000	0.000	0.012

Table 3: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, baseline model (in first differences), one lag. Standard errors are reported in the rows named "s.e.". Bold numbers refer to coefficients that are significant at 0.05 level.

	EC_t	PA_t	RP_t	EC_{t-1}	PA_{t-1}	RP_{t-1}
EC_t	0	0	**-8.680**	-0.069	-0.001	-0.984
s.e.	0	0	2.072	0.067	0.001	1.959
PA_t	2.42	0	-104.139	2.178	0.059	64.278
s.e.	2.249	0	72.963	1.883	0.221	62.720
RP_t	0	0	0	0	0	**0.613**
s.e.	0	0	0	0	0	0.069

Table 4: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, baseline model (in levels), one lag, category: food.

	EC_t	PA_t	RP_t	EC_{t-1}	PA_{t-1}	RP_{t-1}
EC_t	0	0	-41.376	0.872	-0.003	36.969
PA_t	-9.788344	0	-835.1266	7.946211161	0. 628	650.213
RP_t	0	0	0	0.003	-0.00002	1.012

Table 5: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, baseline model (in first differences), one lag, category: clothing.

	EC_t	PA_t	RP_t	EC_{t-1}	PA_{t-1}	RP_{t-1}
EC_t	0	0	-11.288	-0.062	-0.035	1.372
PA_t	0.984	0	-581.317	-0.186	-0.524	310.167
RP_t	0	0	0	-0.002	-0.0002	0.483

Table 6: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, baseline model (in first differences), one lag, category: transports.

	EC_t	PA_t	RP_t	EC_{t-1}	PA_{t-1}	RP_{t-1}
EC_t	0	0	8.862	-0.352	-0.016	-0.033
PA_t	-0.956	0	42.060	-0.355	-0.368	31.911
RP_t	0	0	0	0.007	-0.001	0.049

Table 7: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, baseline model (in first differences), one lag, categories: televisions and telecommunications.

	DEC_t	PA_t	RP_t	DEC_{t-1}	PA_{t-1}	RP_{t-1}
DEC_t	0.000	0	-1.608	0.094	-0.0001	-3.288
PA_t	28.081	0	-474.037	7.524	0.051	-293.316
RP_t	0	0	0	-0.003	0.000007	0.267

4.2 Model with EC derivatives

Table 8 displays the results of the estimation of the model with EC derivatives. Switches in Engel curves derivatives significantly and positively influence patent applications: positively within period and negatively with one lag. Notice, however, that the coefficient for the influence of EC on PA are similar between Γ_0 and Γ_1 except for the sign. We also estimate the SVAR model in first differences. Table 9 shows the estimates of the SVAR coefficients for this case. As we can see, changes in Engel curves derivatives are positively associated with changes in patent applications.

We also show the results when the same study is performed separately for specific sets of categories of expenditure (see tables 10, 11, 12, 13). (Again, the choice of taking the data in first differences or in levels is dictated by the presence or not of a unit root). We notice that the sign of the influence between ECs derivative and patent application is not constant across the different sectors: negative as regards food and clothing, positive as regards transports, televisions and telecommunications. This suggests, on the one hand, some evidence for the "escaping satiation hypothesis" (i.e. the hypothesis that firms attempt to escape satiation of needs and wants by offering more innovative products). On the other hand, it seems that the same hypothesis is not confirmed for all sectors of consumption and production.

Table 8: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, model with derivatives (in levels), one lag. Standard errors are reported in the rows named "s.e.". Bold numbers refer to coefficients that are significant at 0.05 level.

	DEC_t	PA_t	RP_t	DEC_{t-1}	PA_{t-1}	RP_{t-1}
DEC_t	0	0	0	**0.973**	0	-0.001
s.e.	0	0	0	0.015	0	0.003
PA_t	**426.038**	0	**-119.051**	**-424.654**	**0.993**	**119.585**
s.e.	144.747	0	57.795	146.562	0.034	59.816
RP_t	-0.081	0	0	0.006	0	**1.019**
s.e.	0.248	0	0	0.244	0	0.011

Table 9: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, model with derivatives (in first differences), one lag. Standard errors are reported in the rows named "s.e.". Bold numbers refer to coefficients that are significant at 0.05 level.

	DEC_t	PA_t	RP_t	DEC_{t-1}	PA_{t-1}	RP_{t-1}
DEC_t	0	0	0	**-0.514**	0	**-0.037**
s.e.	0	0	0	0.066	0	0.016
PA_t	**695.511**	0	-92.767	328.863	0.061	48.890
s.e.	189.490	0	74.4	171.611	0.218	63.264
RP_t	0.007	0	0	0.021	0	**0.615**
s.e.	0.237	0	0	0.195	0	0.065

Table 10: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, model with derivatives (in levels), one lag, category: food.

	DEC_t	PA_t	RP_t	DEC_{t-1}	PA_{t-1}	RP_{t-1}
DEC_t	0	0	0	0.112	0.000	-0.105
PA_t	-952.364	0	-1143.084	697.288	0.058	936.808
RP_t	0.124	0	0	0.821	0.000	1.041

Table 11: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, model with derivatives (in first differences), one lag, category: clothing.

	DEC_t	PA_t	RP_t	DEC_{t-1}	PA_{t-1}	RP_{t-1}
DEC_t	0	0	0	-0.547	0.000	0.036
PA_t	-110.663	0	245.579	-102.956	-0.335	-106.400
RP_t	0.094	0	0	0.195	0.000	0.504

4.3 Model with inequality index

Table 14 displays the results of the estimation of the model with inequality index, i.e. the Gini coefficient calculated for each category of expenditure for each time period. We find a small, but significant and positive, causal influence from patent application at time $t-1$ to inequality at time t. We also find that when we control for inequality instead of relative prices, the link between EC position and innovative activity becomes positive.

Table 12: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, model with derivatives (in first differences), one lag, category: transports.

	DEC_t	PA_t	RP_t	DEC_{t-1}	PA_{t-1}	RP_{t-1}
DEC_t	0	0	0	-0.568	0.000	-0.010
PA_t	525.757	0	-54.384	296.606	-0.498	37.441
RP_t	-0.074	0	0.000	-0.416	0.000	0.015

Table 13: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, model with derivatives (in first differences), one lag, categories: televisions and telecommunications.

	DEC_t	PA_t	RP_t	DEC_{t-1}	PA_{t-1}	RP_{t-1}
DEC_t	0.000	0	0.000	-0.514	0.000	-0.025
PA_t	1603.240	0	-1391.387	4267.306	0.030	-149.943
RP_t	1.866	0	0.000	0.490	0.000	0.338

Table 14: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, model with inequality index (in levels), one lag. Standard errors are reported in the rows named "s.e.". Bold numbers refer to coefficients that are significant at 0.05 level.

	EC_t	PA_t	$INEQ_t$	EC_{t-1}	PA_{t-1}	$INEQ_{t-1}$
EC_t	0	0	-3.630	**0.994**	0	3.570
s.e.	0	0	7.233	0.005	0	6.646
PA_t	**5.823**	0	39.711	**-5.761**	**0.992**	-23.725
s.e.	1.962	0	203.038	1.990	0.034	198.057
$INEQ_t$	0	0	0	0.006	**0.000008**	**0.834**
s.e.	0	0	0	0	0.000	0.033

Table 15: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, model with inequality index (in first differences), one lag. Standard errors are reported in the rows named "s.e.". Bold numbers refer to coefficients that are significant at 0.05 level.

	EC_t	PA_t	$INEQ_t$	EC_{t-1}	PA_{t-1}	$INEQ_{t-1}$
EC_t	0	0	-0.007	0.015	-0.001	-0.174
s.e.	0	0	6.817	0.071	0.002	4.357
PA_t	1.743	0	137.971	2.198	0.055	-54.647
s.e.	2.284	0	202.598	1.999	0.221	103.177
$INEQ_t$	0	0	0	-0.001	0.000	-0.104
s.e.	0	0	0	0.001	0.000	0.078

5 Conclusions

Consumer expenditure is the large component of the gross domestic product and demand. As such, its influence on firms inventive activity have important consequences for the structure and growth of domestic industry. This study has empirically examined the existence of causal relationship between changes in consumer expenditure patterns and innovative activity. Our results suggest that, in the case of UK economy, there is indeed

Table 16: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, model with inequality index (in levels), one lag, category: food.

	EC_t	PA_t	$INEQ_t$	EC_{t-1}	PA_{t-1}	$INEQ_{t-1}$
EC_t	0	0	-8.961	0.840	0.0005	20.268
PA_t	-5.229	0	1839.468	5.087	0.564	-638.586
$INEQ_t$	0	0	0	0.0001	0.00007	0.673

Table 17: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, model with inequality index (in first differences), one lag, category: clothing.

	EC_t	PA_t	$INEQ_t$	EC_{t-1}	PA_{t-1}	$INEQ_{t-1}$
EC_t	0	0	99.519	0.152	-0.041	17.471
PA_t	4.386	0	-506.958	0.106	-0.197	-157.575
$INEQ_t$	0	0	0	-0.001	0.00006	-0.128708

Table 18: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, model with inequality index (in first differences), one lag, category: transports.

	EC_t	PA_t	$INEQ_t$	EC_{t-1}	PA_{t-1}	$INEQ_{t-1}$
EC_t	0	0	3.834	-0.293	-0.024	-2.45
PA_t	-0.028	0	-665.787	1.154	-0.812	-5.907
$INEQ_t$	0	0	0	0.001	-0.0006	-0.066

Table 19: Estimates of the SVAR coefficient matrices Γ_0 and Γ_1, model with inequality index (in first differences), one lag, categories: televisions and telecommunications.

	EC_t	PA_t	$INEQ_t$	EC_{t-1}	PA_{t-1}	$INEQ_{t-1}$
EC_t	0	0	19.845	0.152	0.0002	-3.270
PA_t	0.479	0	-86.564	21.211	0.081	-218.073
$INEQ_t$	0	0	0	0.00063	0.000007	-0.108

positive and significant relationship. Precisely, an increase in the marginal propensity to consume a particular product causes positive responses by firms-producers in the form of increase of inventive activity. This provides some confirmation of *demand pull* innovations hypothesis. We also expressly call for a better understanding of the role of domestic consumption in triggering firms innovations.

References

Bils, M. and P. J. Klenow (2001). The acceleration in variety growth. *The American Economic Review 91*(2), 274–280.

Bruns, S. B. and A. Moneta (2016). Intertemporal propensity to consume. *Journal of Evolutionary Economics*, 1–20.

Cainelli, G., R. Evangelista, and M. Savona (2006). Innovation and economic performance in services: a firm-level analysis. *Cambridge Journal of Economics 30*(3), 435–458.

Chai, A. and A. Moneta (2012). Back to Engel? some evidence for the hierarchy of needs. *Journal of evolutionary economics 22*(4), 649–676.

Crespi, G., C. Criscuolo, and J. Haskel (2008). Productivity, exporting, and the learning-by-exporting hypothesis: direct evidence from uk firms. *Canadian Journal of Economics/Revue canadienne d'économique 41*(2), 619–638.

Dosi, G. (1988). Sources, procedures, and microeconomic effects of innovation. *Journal of economic literature*, 1120–1171.

Engel, E. (1857). Die Produktions- und Consumtionsverhältnisse des Königreichs Sachsen. *Zeitschrift des Statistischen Bureaus des Koniglich Sachischen Ministeriums des Innern 8 and 9*.

Fan, J. (1993). Local linear regression smoothers and their minimax efficiency. *Annals of Statistics 21*, 196–216.

Fan, J. and I. Gijbels (1992). Variable bandwidth and local linear regression smoothers. *Annals of Statistics 20*, 2008–2036.

Fan, J. and I. Gijbels (2003). *Local Polynomial Modelling and Its Applications*. Chapam & HallCRC.

Gasser, T. and H. Müller (1979). Kernel estimation of regression functions. In T. Gasser and M. Rosenblatt (Eds.), *Smoothing Techniques for Curve Estimation*, pp. 23–68. Springer-Verlag.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature 28*(4), 1661–1707.

Kleinknecht, A. and B. Verspagen (1990). Demand and innovation: Schmookler re-examined. *Research policy 19*(4), 387–394.

Licht, G., G. Ebling, N. Janz, and H. Niggemann (1999). Innovation in the service sector–selected facts and some policy conclusions. *Center for European Research, Manheim, December*.

Moneta, A. and A. Chai (2014). The evolution of Engel curves and its implications for structural change theory. *Cambridge journal of economics 38*(4), 895–923.

Moneta, A., D. Entner, P. O. Hoyer, and A. Coad (2013). Causal inference by independent component analysis: Theory and applications. *Oxford Bulletin of Economics and Statistics 75*(5), 705–730.

Nadaraya, E. (1964). On estimating regression. *Theory of Probability and its Applications 9*(1), 141–142.

Pasinetti, L. (1981). *Structural Change and Economic Growth*. Cambridge University Press, Cambridge.

Rosenberg, N. (1976). *Perspectives on Technology*. Cambridge University Press, Cambridge.

Scherer, F. M. (1982). Demand-pull and technological invention: Schmookler revisted. *The Journal of Industrial Economics*, 225–237.

Schmookler, J. (1966). *Invention and economic growth*. Harvard University Press, Cambridge.

Shimizu, S., P. O. Hoyer, A. Hyvärinen, and A. Kerminen (2006). A linear non-Gaussian acyclic model for causal discovery. *Journal of Machine Learning Research 7*, 2003–2030.

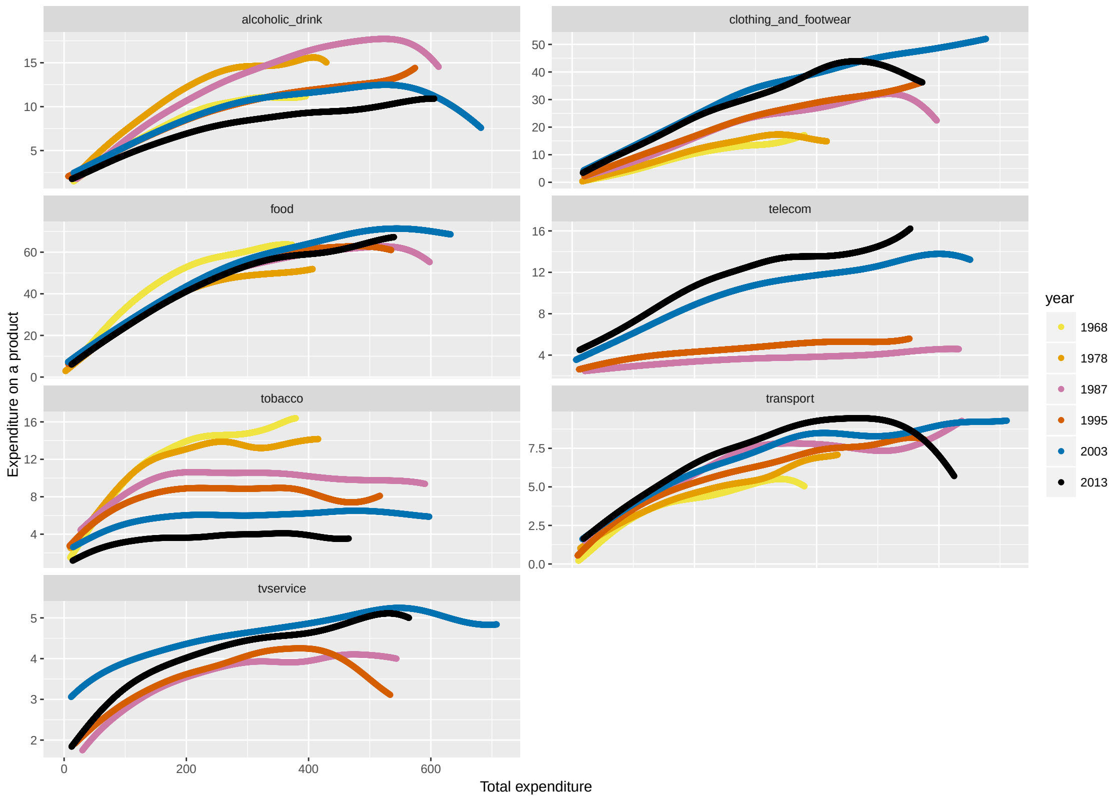
Stoneman, P. (1979). Patenting activity: A re-evaluation of the influence of demand pressures. *The Journal of Industrial Economics*, 385–401.

Von Hippel, E. (1986). Lead users: a source of novel product concepts. *Management science 32*(7), 791–805.

Von Hippel, E. (2005). Democratizing innovation: The evolving phenomenon of user innovation. *Journal für Betriebswirtschaft 55*(1), 63–78.

Watson, G. (1964). Smooth regression analysis. *Sankhyā: The Indian Journal of Statistics, Series A 26*(4), 359–372.

Figure 1: Evolution of Engel curves over time



Note: Total and specific expenditures are expressed in pounds and have been deflated using the RPI (base year, 1987). Expenditure represents real biweekly household spending expressed in pounds.

Figure 2: Time series of derivatives of Engel curves (average position) for different consumption categories and the number of patent applications in the corresponding manufacturing/service sector