CESifo WORKING PAPERS

6946
2018

March 2018

Assessing Temporary Product-Specific Subsidies: A Time Series Intervention Analysis

David Leuwer, Bernd Süssmuth

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl
www.cesifo-group.org/wp

An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: www.CESifo-group.org/wp

CESifo *Working Paper No. 6946*
Category 6: Fiscal Policy, Macroeconomics and Growth

Assessing Temporary Product-Specific Subsidies: A Time Series Intervention Analysis

Abstract

We propose an analytical framework based on the Kalman Filter to quantify central distortionary effects of product-specific subsidies. In our application, we use time series of foreign and domestic order book levels during and after the temporary installation of a "cash for clunkers" subsidy by the German government in 2009 to assess implied disruptions in the German automobile sector and eleven competing industries of the German manufacturing sector. We find stimulus-effects to be rather mild, some evidence of intertemporal program reversal, and consumers' windfall gains to clearly come at the expense of other industries.

JEL-Codes: E320, E620, L620, C320.

Keywords: automobile industry, regime changes, counterfactual analysis.

David Leuwer
University of Leipzig
Institute for Empirical Research in Economics
Grimmaische Str. 12
Germany – 04109 Leipzig
davidleuwer@hotmail.com

*Bernd Süssmuth**
University of Leipzig
Institute for Empirical Research in Economics
Grimmaische Str. 12
Germany – 04109 Leipzig
suessmuth@wifa.uni-leipzig.de

*corresponding author

We thank Jesus Crespo Cuaresma, Christian Hutter, Christian Merkl, Willi Semmler, Thomas Steger, Roman Stöllinger, Marco Sunder, Timo Trimborn, Enzo Weber, and participants of the IWH Workshop on Fiscal Policy and the Great Recession, of the Recent Developments in Macroeconomics Conference at ZEW Mannheim, the 'Modelling regime changes' session of the International Conference on Computational and Financial Econometrics (CFE), and of seminars at Vienna University of Economics and Business, IAB/University of Erlangen-Nuremberg, and the University of Leipzig for many valuable comments and suggestions.

1 Introduction

The debate about fiscal stimulus or in general about the government "buying output" and the size, impact, and timing of the multiplier of government spending has a long tradition, in particular, in the quantitative economics literature. Seminal theoretical contributions, taking a supply-side perspective on the topic, include Hall (2009), Angeletos and Panousi (2009), and Strulik and Trimborn (2017). Demand-sided quantitative research focusing on macroeconomic aggregates can be found, among others, in the seminal studies by Blanchard and Perotti (2002), Barro and Redlick (2011), and Ramey (2011). In the context of an industry with high fixed costs total market demand and price are of paramount importance as they largely determine (annual) profitability; see Goolsbee and Krueger (2015) on the U.S. lightweight vehicle industry. Product-specific fiscal stimulus in the vehicle sector of some G7 economies is analyzed, for example, in Adda and Cooper (2000) for France, Schiraldi (2011) for Italy, and in Mian and Sufi (2012) and, to some extent, Goolsbee and Krueger (2015) for the U.S., respectively. We take up the discussion with a different twist, propose a novel analytical framework to quantify intertemporally *and* intersectorally distortionary effects of such subsidies, and come up with some new insights.

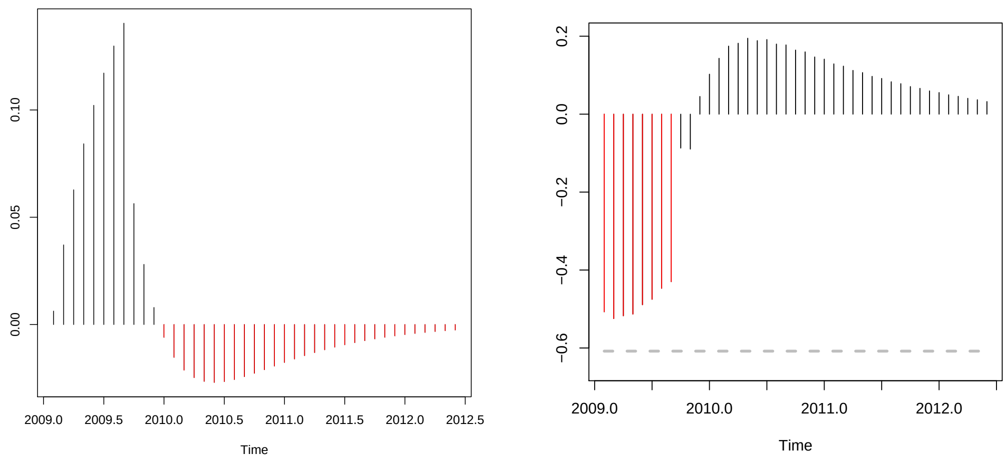
The 2015-2017 "dieselgate" emission control cheating-scandal concerning leading German automobile firms and their products since 2009, led some German politicians to propose a quite specific scrapping subsidy to foster purchases of new diesel vehicles meeting the Euro-6 emission standard. The latter sets the currently highest standard of acceptable limits for exhaust emissions of new diesel vehicles in the European Union as of 2014. The German Federal Ministry of the Environment as well as politicians from both the liberal and the green party clearly reject this idea on grounds of addressing the problem by unjustifiably favoring a dying out technology at the cost of other products –such as e-vehicles, public transport or bikes– and of the taxpayers. This example very well highlights the three dimensions of product-specific scrapping subsidies that we seek to explore and quantify: demand-sided effectiveness, intertemporal bias, and intersectoral bias. A comprehensive quantitative analysis may also help us to address the question of a trade-off between effectiveness on the one hand and intertemporal and intersectoral bias on the other; that is, if a product-specific scrapping subsidy is merely (very) effective does this imply low (high) intertemporally and intersectorally distortionary effects of the measure?

To this end, we analyze the temporary installation of a "cash for clunkers" subsidy by the German government in 2009 that coincided with the perceived need for fiscal stimulus in the advent of the Great Recession. As orders and sales of the manufacturing industries started to decrease exceptionally,[1] the German government decided to introduce a scrapping bonus as part of its recovery program "*Konjunkturpaket* II" in January 2009. From the 50bn Euros of the total package, 5bn Euros financed the cash for clunkers program (OECD, 2010, p. 100). The individual scrapping bonus amounted to 2,500 Euros. It was granted to private consumers for scrapping a used car and buying a new one. Although, it was officially labeled an environmental policy measure, with the aim to increase the fuel efficiency of the German households' vehicle stock, there is little debate that it was indeed an example for counter-cyclical fiscal policy with the aim to cushion the crisis' negative effects on the German automobile industry. The latter is said to be the nation's core industry directly employing about two percent of the German working population (Schweinfurth, 2009; Leuwer and Süssmuth, 2018). Microeconomically, the scrapping bonus has three main effects. First, it increases the disposable income of households (primary income effect). Secondly, it reduces the price of automobiles (price effect). And thirdly, it decreases disposable income in case it has to be financed via taxation (withdrawal effect). The price effect may be subdivided into a substitution and a secondary income effect. One problem of the scrapping bonus is that due to the substitution effect it will probably increase the quantity demanded in the automobile industry at the expense of other industries, i.e. induce an intersectoral bias. Besides, only a small fraction of car sales in 2009 might have been induced by the bonus. A major share of vehicle sales might have been carried out anyway. We can think of realized bonuses in this case as unintended windfall gains. The higher they are, the less effective we overall assess the scrappage scheme. Finally, intertemporal bias is given if consumers "squirrel away" new cars to realize bonuses; that is, households that had planned to buy a new car in 2010 or later might have simply pulled their purchase from the future to the present (strategic pull-forward effects). Mian and Sufi (2012) refer to this phenomenon as "program reversal." This reversal in turn might lead to a deterioration of vehicle sales after the end of the scrapping bonus. Such an effect has, for example, been found in the aftermath of similar policy measures in Italy and France (Adda and Cooper, 2000). By estimating counterfactual outcomes based on information contained in foreign orders and netting out reaction functions, our study

[1] However, in international terms the dip was rather modest. Only car sales growth in Poland and China reacted even less negatively than the German one from 09/08 to 01/09; see OECD (2010, p.95).

is the first to offer detailed quantitative assessments of demand-sided effectiveness, intertemporal bias, and intersectoral bias of a product-specific scrappage subsidy. A sneak preview of our results section given in Figure 1 makes the point: demand-sided effectiveness is shown in the black colored part of its left panel; intertemporal bias in the form of program reversal is represented by the red part in the left schedule (in particular, seen against the backdrop of the black colored area in the right panel, i.e. a swelling pent-up demand in all other industries, apart from automobiles, coinciding with the ending of the subsidy); intersectoral bias even outnumbering the first effect as highlighted by the red colored area in its right panel.

Figure 1: Distortionary effects of product-specific subsidy on order books



Note: Left panel: automobile sector; right panel: all other manufacturing sectors; period: 01/2009 to 06/2012

The German 2009 scrappage program that was the most generous as a share of domestic GDP, amounting to 0.2 percent, in an international comparison is indeed perceived to profoundly have stabilized sales (OECD, 2010). However, we find the demand-sided effectiveness of such a temporary product-specific scrappage subsidy to be rather poor. Buyers realize substantial unintended windfall gains that are –as opposed to some alternative schemes one can think of– non-neutral with regard to the public budget. Additionally, stabilization comes according to our estimates at the price of a prolongation of the sectoral trough and a procrastination of the subsequent recovery in the automobile industry by about one year. This seems non-trivial costs given that the German automobile sector's annual turnover amounts to roughly ten percent of German GDP (Schweinfurth, 2009). Finally, as theory suggests, we find evidence for (net) sectoral crowding-out and, hence, intersectoral bias of the measure. Thus, our summarizing findings-preview might be seen as speaking in favor of less product-specific alternatives to induce fiscal stimulus such as consumption vouchers with deadlines, tax incentives, or intervention support in the form of direct governmental purchases.

Our contribution to the literature and research agenda is to set up and apply an integrated time series approach to systematically and thoroughly disentangle and quantify the different distortions of temporary product-specific subsidies. To the best of our knowledge, such an approach does not exist to the present. It is based on Kalman Filter/Smoother estimates of counterfactual time series using information contained in series unaffected from the intervention (in our exemplary application, foreign orders) and on netting out corresponding factual and counterfactual response functions.

The remainder is organized as follows. Section 2 briefly rationalizes some theoretical considerations on product-specific subsidization regarding the use of resources and output in the total economy. After some description of our data, we introduce in Section 3 the analytical time series intervention framework to disentangle and quantify the different distortionary effects of temporary product-specific subsidies. In our application we interpret findings step by step. Section 4 concludes.

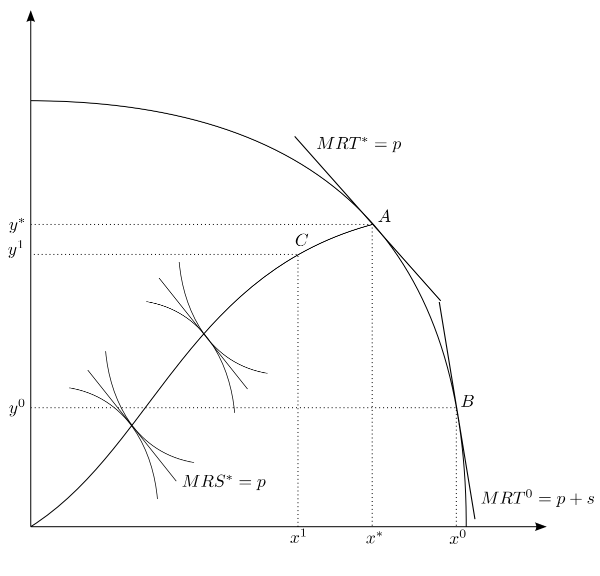
2 Some theoretical considerations

A scrapping bonus is an instrument of fiscal policy that may be used to stabilize an industry in times of economic crisis. To get an idea of the effects of a product-specific scrapping subsidy we consider a basic theoretical model in the spirit of Harris and Todaro (1970). Detailed underlying equations are given in the Appendix. In the following, we focus on a graphical wrap-up as shown in Figure 2.

Suppose the total economy initially produces efficiently in point A with output x^* and y^*, where the latter subsumes the output of all other sectors apart from x. Input factors are rewarded their marginal product m in each sector x and remaining industries y. The introduction of a subsidy s for sector x, e.g. a scrapping bonus, will increase the demand for resources and ultimately raise output in sector x at the expense of remaining sectors y. The economy will produce in B (mere substitution effect). Note that a production in B cannot be Pareto-efficient as $MRS^* \neq MRT^0$. In case the subsidization of sector x

ends, output in sector x (all other sectors y) will decrease (increase).[2] Temporarily this can lead to a situation where there are unused resources. Graphically such a situation is given by point C. For R_0, production in C would be feasible, however, inputs are not fully employed, i.e. production does not fulfill technical efficiency. Eventually, as m_y decreases the economy will reach a new productively efficient equilibrium with all resources in use. Thus, the challenge is to quantifying distance AB and the associated drop in y and increase in x over time of the transitory x-specific subsidy; distance BC, that is the gradual decrease in x at the end and after removal of the subsidy possibly falling below Pareto-level x^* to x^1; distance CA, that is the recovery to initial levels x^*, y^*. Note this process –other than shown in Figure 2– might be paralleled by some pent-up demand in y (graphically, this would imply that the concave connecting line between C and A would temporarily even exceed y^*). The final task is to assess the time it takes for re-allocating, that is for the BC, CA re-adjustment.

Figure 2: Transformation curve and change in sectoral output due to subsidy



In the empirical application parts of our study, inefficiency will be measured by estimating a counterfactual scenario without a scrapping bonus. It allows us not only to assess how close to the origin and, hence, off x^* the output in the German automobile sector fell below an efficient level after the ending of the program, but also to assess the price, i.e. the repercussion, of this fiscal stimulus in terms of getting back to an efficient level x^*. In other words, our strategy allows us to measure the true stimulus of

[2]In the simple underlying model detailed in the Appendix this is due to equation (A.1.9).

the program and the true dip in vehicle sales after the ending of the cash for clunkers program. Additionally, it will provide us with a measure for the actual time of recovery from this dip, i.e. the time elapsed for distance CA in Figure 2. By "true" and "actual" in the last sentences we mean corrected distance and time measures: First, this refers to distance $x^0 - x^*$ corrected for unintentional windfall-profit effects, i.e. considering the volume of vehicles that would have been produced and sold between January and September 2009 anyway without the subsidy. Secondly, it refers to corrected distance and time elapsed measures for $x^* - x^1$ taking into account strategic pull-forward effects, i.e. considering consumers having pulled forward their purchases from the future. Naturally, such purchases deepen the cut of sales after the ending of a scrappage scheme and delay subsequent recovery.

3 Empirical framework and analysis

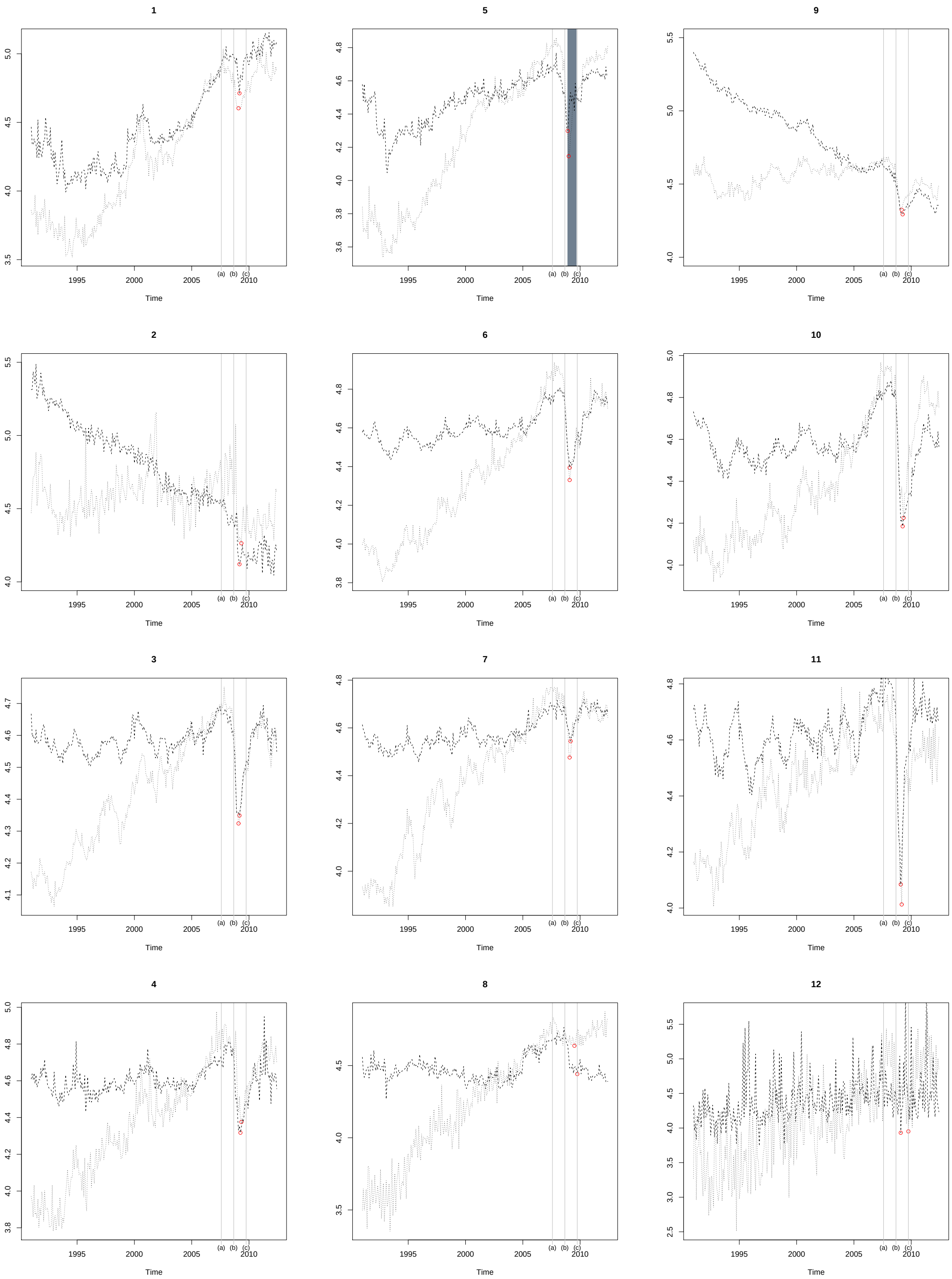
3.1 Sectoral time series

We consider seasonally adjusted monthly data from January 1991 to June 2012[3] on order book levels in twelve industries of the German manufacturing sector. The data is supplied as volume index by the German Statistical Office. The industries that are considered are electronical and optical devices, clothing, chemicals, electronics, cars, metalworking, production of paper, pharmaceutics, textiles, machines, production of metal, and vehicles other than cars. Figure A.5 shows the data for the twelve considered industries separated by orders from foreign markets (dotted) and from inland (dashed). The three vertical grey lines mark the beginning of the financial crisis on August 9, 2007 (hallmarking the start of rapid increase of the interbank interest rate in the U.S.),[4] the collapse of Lehman Brothers in September 2008, and the beginning of the sovereign debt crisis in the euro area in October 2009, respectively.

[3]We choose June 2012 as endpoint of our sample period as it generally marks a point of discontinuation of the official statistics on industrial new orders and corresponding sectoral series in European countries. See De Bondt et al. (2013) for detail.

[4]Different to the situation at the time in the U.S., where subprime auto credit had been unsustainably inflated by the preceding housing and credit bubble (Goolsbee and Krueger, 2015), neither credit crunch in the sense of households lacking access to credit and, thus, postponing car purchases nor the liquidation risk of the "big 3" car producers were given for Germany (OECD, 2010).

Figure 3: Log order book levels with foreign (dotted) and inland (dashed) origin



Note: German manufacturing sectors: 1 Electronical and optical devices, 2 Clothing, 3 Chemicals, 4 Electronics, 5 Cars (shaded area: scrappage program period), 6 Metalworking, 7 Production of paper, 8 Pharmaceutics, 9 Textiles, 10 Machines, 11 Production of metal, 12 Vehicles other than cars; period: 01/2009 to 06/2012.

The grey shaded area in the fifth panel identifies the scrapping bonus in the cars industry that was in place from January 2009 to September 2009. In each panel the two red points mark lower turning points, i.e. the minimum of orders between the first and third vertical line, respectively. As can be seen from Figure 3, the crisis effect varies by sector. There seem to be three stylized types of reaction: industries that are seemingly unaffected by the crisis (e.g. vehicles other than cars in panel 12), industries that were affected by the crisis but recovered quite fast (e.g. electronics in panel 4) and industries in which orders shifted downwards and did not recover up to the end of our observation period (e.g. clothing in panel 2).

The German cars industry is the only one from the sectors shown in Figure 3 that could directly benefit from policy measures undertaken to dampen the crisis' impact. Although the bonus was officially introduced to increase fuel efficiency of the German households' vehicle stock, there is no doubt it actually was intended as fiscal stimulus. Table A.1 in the Appendix provides summary statistics of series underlying Figure 3.

3.2 Intervention analysis

Intervention analysis, dating back to the seminal contribution by Box and Tiao (1975), is a straightforward technique to backup our approach and allows to assess the effect of an intervention on a series, in particular, as regards potential change of its first moment. Consider a time series $\{y_t\}$ that may be modeled by some ARIMA(p, d, q) process. An intervention model then is written as

$$y_t = \nu(L)I_t + \frac{\Theta_q(L)}{\Phi_p(L)}z_t = m_t + n_t. \tag{3.1}$$

In (3.1) n_t is the noise model and m_t represents the change in the mean function due to an intervention. The lag polynomial $\nu(L)$ determines the shape and the duration of the series' reaction to a shock. $\nu(L)$ is approximated by the following rational function

$$\nu(L) = \frac{\omega(L)}{\delta(L)}L^a, \tag{3.2}$$

where the exponent $a \in \mathbb{N}_0$ determines the amount of time that passes before y_t reacts to an intervention; and $\omega(L)$ and $\delta(L)$ are polynomials in L of order s and r, i.e. $\omega(L) = \omega_0 + \omega_1 L + ... + \omega_s L^s$ and $\delta(L) = 1 - \delta_1 L - ... - \delta_r L^r$. The coefficients ω_j in the numerator of (3.2) capture the immediate effect of an intervention while the coefficients δ_r of the denominator model the permanent effect of the intervention.

Coefficients ν_j of $\nu(L)$ are calculated from $\delta(L)\nu(L) = \omega(L)L^a$, that is

$$(1 - \delta_1 L - ... - \delta_r L^r)(\nu_0 + \nu_1 L + \nu_2 L^2 + ...) = (\omega_0 + \omega_1 L + ... + \omega_s L^s)L^a.$$

This implies that

$$\nu_j = \begin{cases} 0 \text{ for } j < d \\ \delta_1\nu_{j-1} + \delta_2\nu_{j-2} + ... + \delta_r\nu_{j-r} + \omega_{j-d} \text{ for } j = d, d+1, .., d+s \\ \delta_1\nu_{j-1} + \delta_2\nu_{j-2} + ... + \delta_r\nu_{j-r} \text{ for } j > d+s. \end{cases}$$

In general, we can think of three different stylized types of intervention responses:

1. Impulse function (IF)

$$I_t := \epsilon_t^{(\tau)} = \begin{cases} 1 \text{ for } t = \tau \\ 0 \text{ for } t \neq \tau, \end{cases} \tag{3.3}$$

2. Extended impulse function (EIF)

$$I_t := \eta_t^{(\tau_1,\tau_2)} = \begin{cases} 1 \text{ for } \tau_1 \leq t \leq \tau_2 \\ 0 \text{ for } t \text{ else}, \end{cases} \tag{3.4}$$

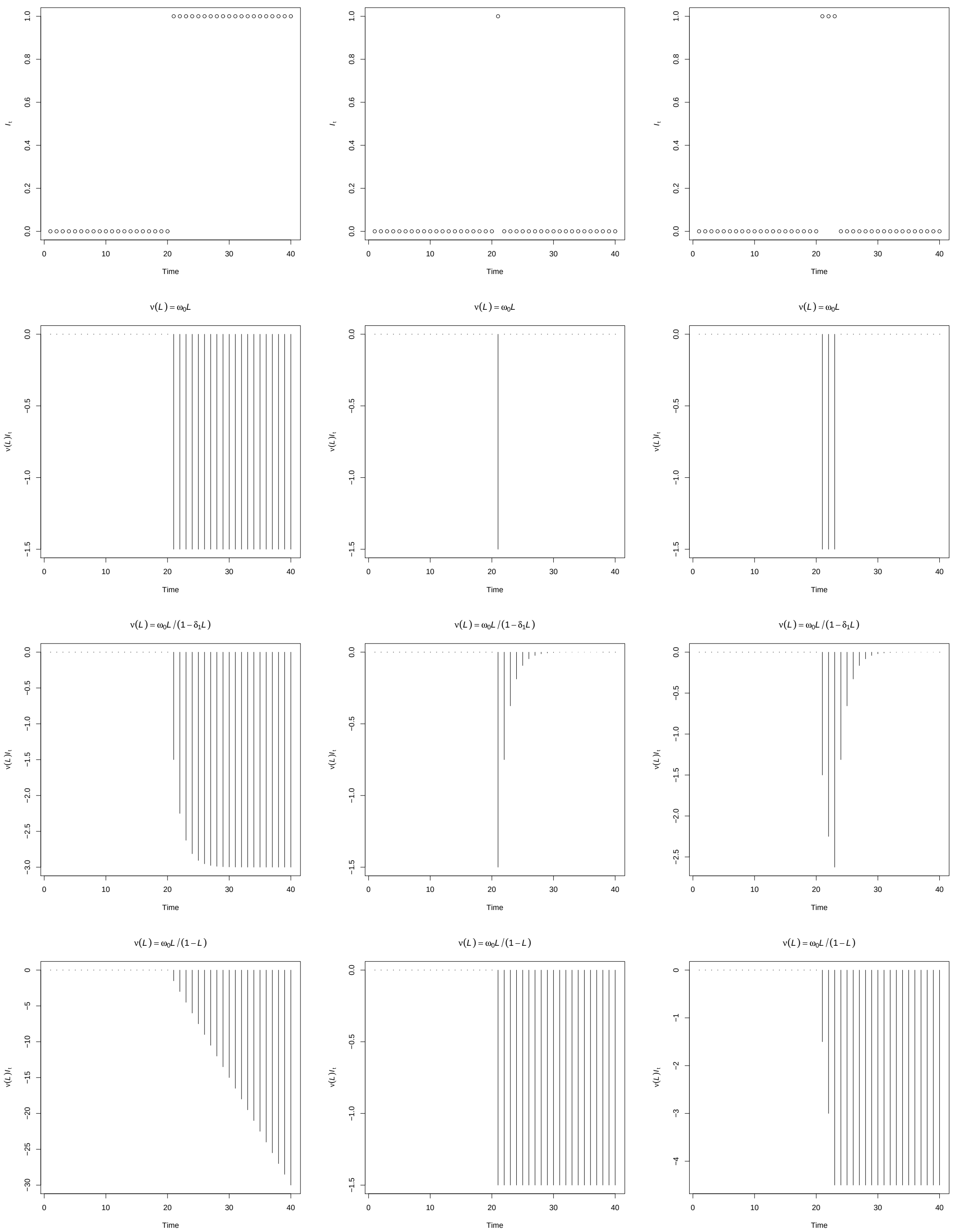
3. Step function (SF)

$$I_t := \zeta_t^{(\tau)} = \begin{cases} 1 \text{ for } t \geq \tau \\ 0 \text{ for } t < \tau. \end{cases} \tag{3.5}$$

Figure 4 exemplarily shows the shape of m_t for different intervention response types along its column dimension: SF: $I_t := \zeta_t^{(\tau)}$ in its first column, IF: $I_t := \epsilon_t^{(\tau)}$ in its second column, and EIF: $I_t := \eta_t^{(\tau_1,\tau_2)}$ in its third column, respectively. Transfer function specifications are displayed along the row dimension: $\nu(L) = \omega_0 L^a$ with $a = 0$ and $\omega_0 = (-1.5)$ in the second row, $\nu(L) = \omega_0/(1 - \delta_1 L)L^a$ with $a = 0$, $\omega_0 = (-1.5)$ and $\delta_1 = 0.5$ in the third row, $\nu(L) = \omega_0/(1 - \delta_1 L)L^a$ with $a = 0$, $\omega_0 = (-1.5)$ and $\delta_1 = 1.0$ in the fourth row, respectively.[5] The fitting of intervention models to data evolves according to the following steps:

[5] In some cases more sophisticated multiple intervention models will be needed in order to consider more complicated (i.e. less stylized) dynamic reactions.

Figure 4: Mean reaction to different intervention types and transfer functions



Notes: First column: $I_t := \zeta_t^{(\tau)}$, second column: $I_t := \epsilon_t^{(\tau)}$, third column: $I_t := \eta_t^{(\tau_1,\tau_2)}$. Second row: $\nu(L) = \omega_0 L^a$ with $a = 0$ and $\omega_0 = (-1.5)$, third row: $\nu(L) = \omega_0/(1 - \delta_1 L)L^a$ with $a = 0$, $\omega_0 = (-1.5)$ and $\delta_1 = 0.5$, fourth row: $\nu(L) = \omega_0/(1 - \delta_1 L)L^a$ with $a = 0$, $\omega_0 = (-1.5)$ and $\delta_1 = 1.0$.

1. Find an ARIMA(p, d, q)-process of appropriate order for the noise model n_t based on the pre-intervention data. Determining the model order (p, q) is done by looking at the sample autocorrelation function (SACF) and sample partial autocorrelation function (SPACF) or minimizing some information criterion.

2. Selecting the intervention type as well as the form of the transfer function (i.e. specifying m_t) is done by visually inspecting the series under study or making use of any prior knowledge about the intervention process.

3. Parameter estimates are obtained by Maximum Likelihood (ML) estimation.

4. Testing the white noise assumption of model residuals completes the procedure.

In the following, we first estimate intervention models for the non-subsidized sectors. We proceed by fitting intervention models to the subsidized car industry quantifying the crisis effect on foreign orders and the crisis and bonus effect on domestic orders, respectively. In a next step, we make use of the information contained in foreign orders series that were unaffected by the domestic scrappage scheme[6] in order to estimate counterfactual intervention-free reactions sector by sector. This strategy allows us to assess and to separate intertemporal strategic pull-forward effects from unintentional windfall profits and from intersectoral distortions, respectively.

3.3 Fitting intervention models to non-subsidized sectors

The choice of a noise model n_t is based on pre-intervention data ranging from 01/1991 to 07/2007. Appropriate AR and MA orders are found by first inspecting the respective series' SACF and SPACF and then minimizing the AIC over a reasonable range of values for p and q. All series are assumed to be integrated of order one, i.e. $d = 1$.

When setting up m_t we first need to choose the respective intervention type. In most cases the crisis impact is modeled as an EIF $\eta_t^{(\tau_1,\tau_2)}$ with $\tau_1 = 09/2008$ and $\tau_2 = 10/2009$. This seems to be a reasonable choice with regard to the course of the crisis and the

[6]It is noteworthy in this context that the German scrappage scheme preceded all comparable temporary programs in the OECD apart from the one installed in France which, however, represents the smallest among the five largest schemes for year 2009 amounting to less then 8 percent of the German subsidization (Schweinfurth, 2009; OECD, 2010).

shape of the series under study.[7] For most industries we observe a quite instantaneous drop in log new orders after 09/2008. Hence, $a = 0$, see equation (3.2), seems to be justified for the majority of cases. Only in case of the clothing industry the series reaction to the collapse of Lehman Brothers is slightly delayed (i.e. by about two months). Thus, we straightforwardly set $a = 2$ for this sector. As regards the shape of the transfer function $\nu(L)$, fairly parsimonious specifications, like the ones shown in the third row of Figure 4, prove adequate. In some cases a higher order of the polynomial $\delta(L)$, e.g. for industries electronical and optical devices, electronics, and textiles, or multiple intervention models, e.g. for the pharmaceutics and machinery industries, turned out to be the superior specifications.

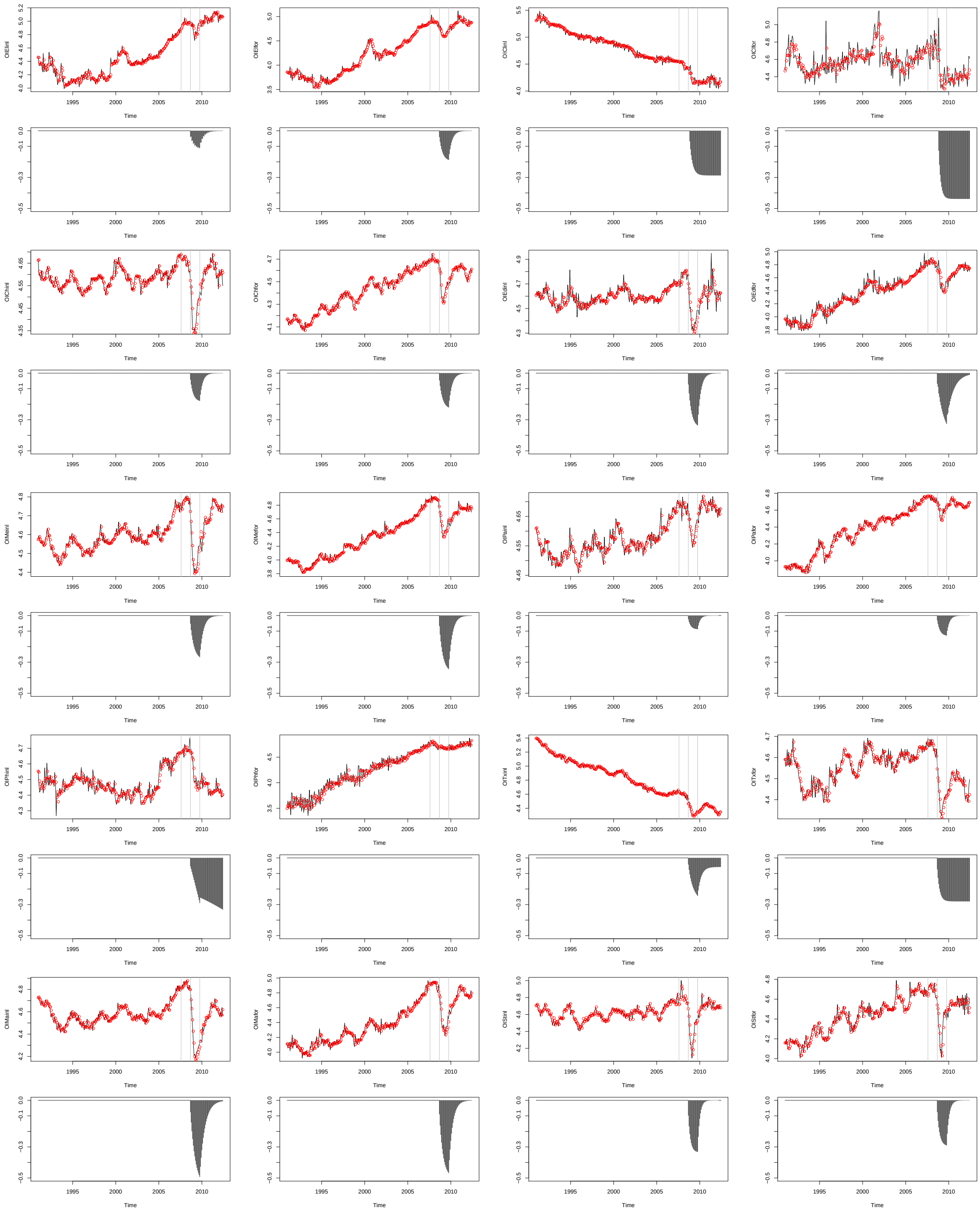
Table A.2 in the Appendix gives an overview on the intervention models fitted to the log series. The last column of the table reports the p-value of the respective Ljung-Box statistic, which was calculated based on 20 lags. The hypothesis that there is no significant residual correlation left cannot be rejected.[8] Figure 5 plots the time series along with fitted values and the respective estimated stylized crisis effect. Table 3.1 reports the estimated (percentage) decrease in vehicle orders due to the crisis k months after 09/2008 for different industries.

Some results stand out. First, in general, orders from abroad seem to have been affected by the crisis more severely than domestic orders. This result fits common wisdom as economies coined by strong exporting industries are generally considered to be most severely hit by an international crisis. One obvious exception is the pharmaceutical industry. Offshore orders in this particular industry seem not to have been affected by the crisis at all, whereas domestic orders decreased significantly and kept on fluctuating around a lower level than before 2008. But also in the electronics, machinery and production of metal industry foreign orders are slightly less affected by the crisis. However, across industries the decrease in foreign orders on average was approximately 13% higher than the one of domestic orders. Secondly, concerning the absolute size of the crisis impact, the German machinery industry was most seriously hit.

[7]However, one might argue that the financial crisis directly carried over into the European sovereign debt crisis. In this case the crisis impact could also be modeled as a step function ζ^{τ} with $\tau = 09/2008$. Eyeballing our series at stake, this seems to be the more appropriate strategy in case of the clothing industry as well as the textiles industry; see panel 2 and 9 in Figure 3.

[8]In other words, the null of the model capturing the dependence structure of the time series cannot be rejected at a 5% level of significance in all but one of the cases.

Figure 5: Log series, fitted values and implied stylized sectoral dips (crisis effect)



Note: Results for the German automobile industry are shown separately in Section 3.4. Industry 12 Vehicles other than cars is not shown due to being not significantly affected by the crisis.

Twelve months after the collapse of Lehman Brothers domestic (foreign) orders had decreased by around 47% (45%). Finally, we can see that there are industries that did not recover up to mid-2012. These are the clothing and textiles industry but also domestic orders in the pharmaceutics and machinery industry and foreign orders in the electronics industry are significantly and persistently lower after than before the crisis. This persistency is is also indicated by $t|_{m_t=0} = \infty$ in the last column of Table 3.1.

Industry No.	Series Name	k										$t\vert_{m_t=0}$
		1	2	3	6	9	12	15	18	21	24	
1	OIElinl	-3.89	-3.64	-6.52	-7.88	-10.27	-10.47	-7.50	-5.19	-2.24	-1.74	29
	OIElfor	-4.01	-7.19	-9.72	-14.59	-17.02	-18.24	-14.84	-7.42	-3.71	-1.86	30
2	OIClinl	0.00	0.00	-6.68	-18.75	-24.20	-26.66	-27.77	-28.27	-28.50	-28.60	∞
	OIClfor	0.00	0.00	-12.80	-32.80	-39.89	-42.40	-43.29	-43.60	-43.71	-43.75	∞
3	OIChinl	-4.11	-7.30	-9.77	-14.32	-16.44	-17.43	-13.78	-6.42	-2.99	-1.39	29
	OIChfor	-4.59	-8.27	-11.21	-16.97	-19.92	-21.44	-17.63	-9.05	-4.65	-2.39	32
4	OIEdinl	-7.23	-12.96	-17.51	-26.24	-30.59	-32.76	-26.61	-13.26	-6.61	-3.30	33
	OIEdfor	-6.81	-8.74	-13.05	-20.50	-26.36	-30.51	-26.73	-20.39	-14.55	-10.61	∞
5	OICainl	See section 3.4										
	OICafor											
6	OIMeinl	-5.13	-9.33	-12.78	-19.82	-23.69	-25.82	-21.87	-12.04	-6.63	-3.65	34
	OIMefor	-6.70	-12.17	-16.64	-25.70	-30.63	-33.32	-28.08	-15.29	-8.33	-4.53	35
7	OIPainl	-2.32	-4.03	-5.29	-7.40	-8.24	-8.58	-6.39	-2.55	-1.02	-0.41	24
	OIPafor	-3.10	-5.46	-7.27	-10.50	-11.93	-12.57	-9.75	-4.33	-1.92	-0.85	26
8	OIPhinl	-5.37	-7.09	-8.83	-14.14	-19.58	-25.17	-25.52	-26.18	-26.85	-27.54	∞
	OIPhfor	-	-	-	-	-	-	-	-	-	-	-
9	OITxinl	-4.21	-7.68	-10.57	-16.69	-20.49	-23.06	-20.79	-13.63	-9.88	-7.91	∞
	OITxfor	-7.35	-12.76	-16.75	-23.44	-26.12	-27.18	-27.61	-27.78	-27.85	-27.88	∞
10	OIMainl	-7.59	-14.17	-19.87	-32.80	-41.21	-46.69	-42.66	-27.77	-18.07	-11.76	∞
	OIMafor	-8.89	-16.20	-22.21	-34.55	-41.41	-45.23	-38.46	-21.38	-11.88	-6.60	38
11	OIStinl	-9.76	-16.67	-21.55	-29.19	-31.89	-32.85	-23.43	-8.30	-2.94	-1.04	27
	OIStfor	-7.57	-13.19	-17.36	-24.45	-27.35	-28.53	-21.45	-8.77	-3.58	-1.46	28
12	OIBoinl	-	-	-	-	-	-	-	-	-	-	-
	OIBofor	-	-	-	-	-	-	-	-	-	-	-

Table 3.1: Crisis effect as percentage drop in orders k months after 09/2008

Note: Last column indicates after how many months the effect has vanished ($= 0$).

3.4 Fitting intervention models to the subsidized sector

3.4.1 Estimating the crisis effect on foreign orders

To model the crisis effect on foreign orders for German vehicles we first choose an ARIMA(2,1,1) process for the noise model n_t. The model order is determined on the basis of a visual inspection of the SACF and SPACF of the pre-intervention data as well as on the basis of the AIC. The change in the series' mean is modeled as $m_t = [\omega_0/(1 - \delta_1 L)]\eta_t^{(\tau_1,\tau_2)}$, with $\tau_1 = 09/2008$ and $\tau_2 = 10/2009$.

Table 3.2 reports the ML estimates for the intervention model fitted to the logs of foreign orders. It can be seen that all coefficient estimates are significant and that the crisis had a significantly negative effect on vehicle orders. The Ljung-Box statistics (calculated for 20 lags) has a p-value $= 0.7119$, i.e. the assumption of white noise residuals cannot be rejected.

The right column of diagrams in Figure 7 shows the log of foreign vehicle orders together with fitted values (upper panel) and the estimated crisis' effect (lower panel)

ϕ_1	ϕ_2	θ_1	ω_0	δ_1
-0.8280	-0.3438	0.3796	-0.0863	0.7139
(0.1711)	(0.0772)	(0.1740)	(0.0210)	(0.0732)
Log-Likelihood = 390.91, AIC = -771.82				

Table 3.2: Intervention model for logs of foreign orders of German automobile sector

Note: Standard errors given in parantheses.

3.4.2 Estimating crisis effect and bonus effect on domestic orders

In order to estimate the crisis effect and the scrapping bonus effect on domestic orders for German cars we have to use a more sophisticated multiple intervention model. We start by fitting an ARIMA(p, d, q) model to the data based on the pre-intervention observations. The model order is chosen as $p = 2$, $d = 1$ and $q = 0$ according to a visual inspection of the SACF and SPACF and the minimization of the AIC.

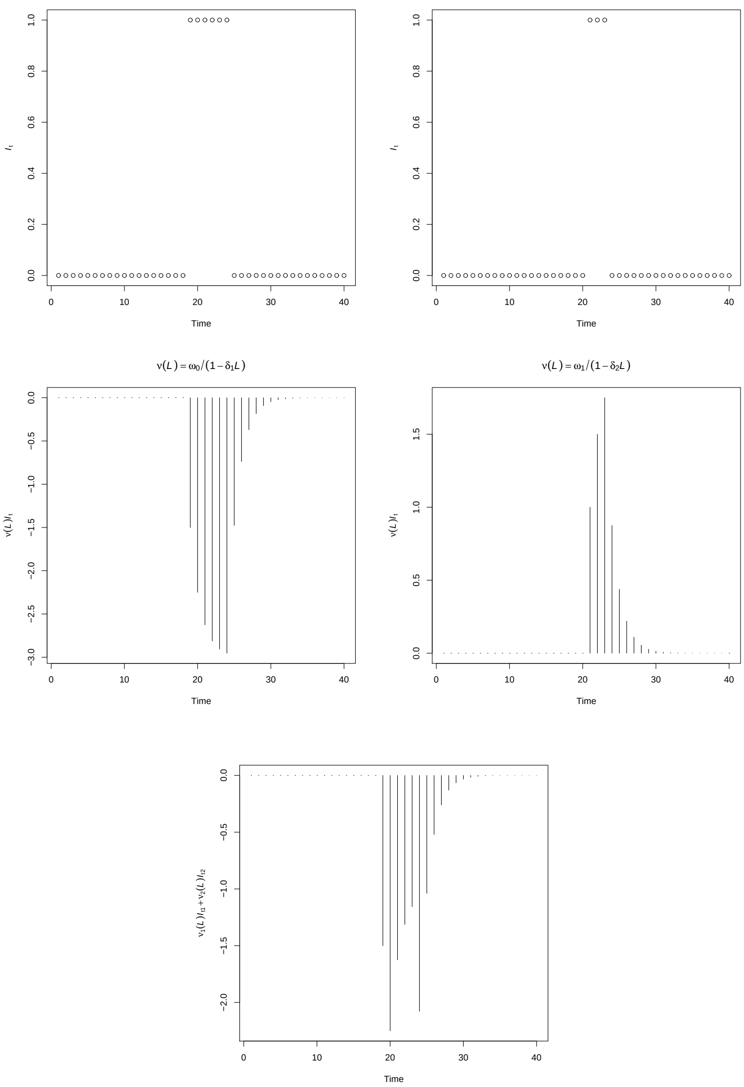
Both the impact of the crisis and the scrapping bonus is modeled as extended impulse function, that is $\eta_{t,1}^{(\tau_1,\tau_2)}$ with $\tau_1 = 09/2008$, $\tau_2 = 10/2009$ and $\eta_{t,2}^{(\tau_1,\tau_2)}$ with $\tau_1 = 01/2009$, $\tau_2 = 09/2009$.

Hence, the change in the mean of domestic orders is assumed to show the following functional form

$$m_t = \frac{\omega_0}{1 - \delta_1 L}\eta_{t,1}^{(\tau_1,\tau_2)} + \frac{\omega_1}{1 - \delta_2 L}\eta_{t,2}^{(\tau_1,\tau_2)}, \tag{3.6}$$

where the first part measures the crisis effect. The second part captures the positive impact of the scrappage bonus. Thus, ω_0 is expected to have a negative sign, while δ_1, ω_1, and δ_2 are presumably positive. The ultimate window of Figure 6 schematically plots the shape of such a specification for m_t given theoretical parameter values.[9]

Figure 6: Stylized transfer functions for crisis effect and scrapping bonus effect



Notes: The following parameter values are assumed: $\omega_0 = (-1.5)$, $\delta_1 = 0.5$, $\omega_1 = 1.0$ and $\delta_2 = 0.5$.

Table 3.3 shows the ML estimates (first row) along with standard errors (second row) for an intervention model as described above fitted to the logs of domestic orders in the German automobile industry. All coefficients are highly significant. As can be seen, the crisis had a significantly negative effect, while the scrapping subsidy effect is significantly positive. The Ljung-Box statistics (calculated for 20 lags) implies a p-value

[9]Note, m_t could be specified in a different way resulting in an even better model fit, yet economically not meaningful coefficients; see Figure A.1 in the Appendix.

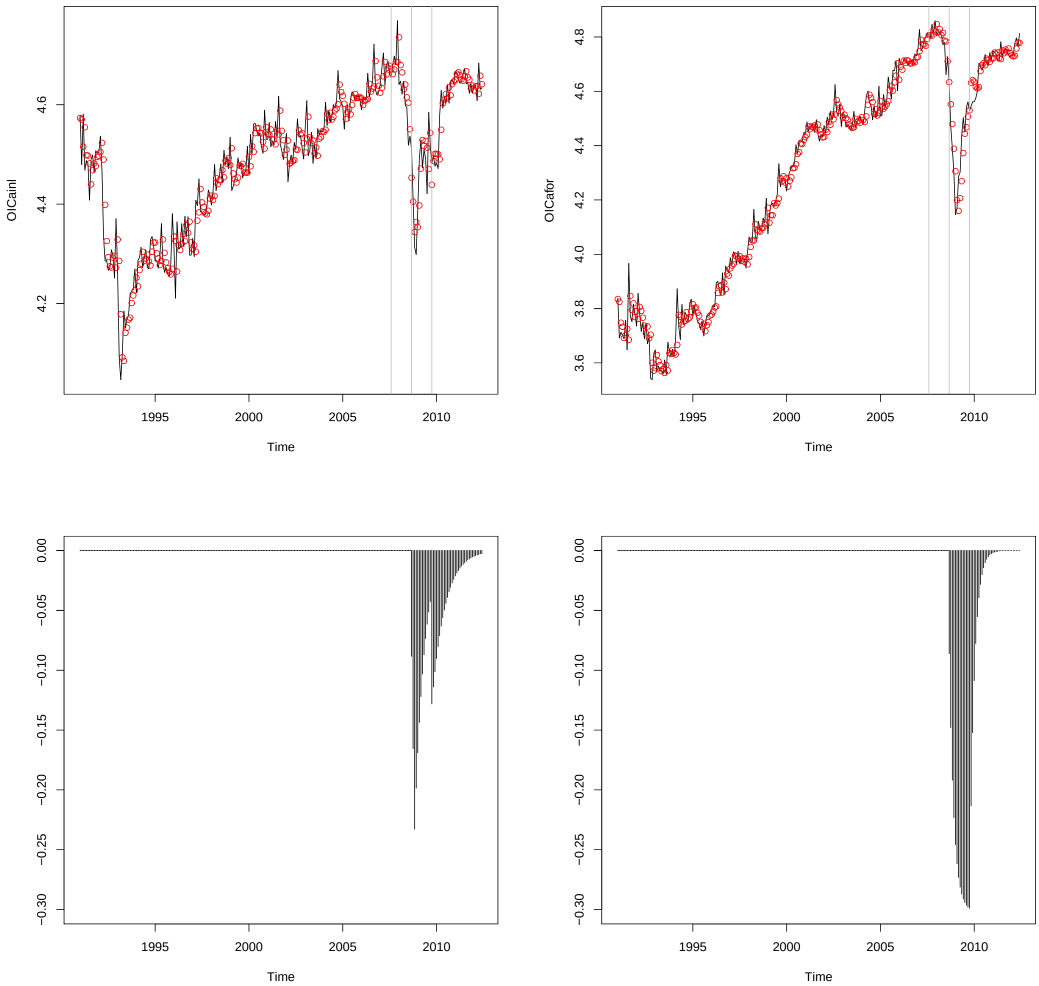
of 0.4309. Thus, the assumption of white noise residuals can also not be rejected.

ϕ_1	ϕ_2	ω_0	δ_1	ω_1	δ_2
-0.4138	-0.1602	-0.0884	0.8725	0.0930	0.8677
(0.0620)	(0.0625)	(0.0189)	(0.1006)	(0.0209)	(0.1431)
Log-Likelihood = 435.56, AIC = -859.12					

Table 3.3: Intervention model for logs of inland orders of German automobile sector.

Note: Standard errors given in parantheses.

Figure 7: Series, fitted values and estimated crisis effect and scrapping bonus effect.



Industry No.	Series Name	k 1	2	3	6	9	12	15	18	21	24	$t\|_{m_t=0}$
5	OICainl	-8.84	-16.55	-23.28	-14.37	-8.72	-5.14	-11.41	-8.02	-5.61	-3.91	41
	OICafor	-8.63	-14.79	-19.19	-26.17	-28.71	-29.64	-21.34	-7.77	-2.83	-1.03	27

Table 3.4: Crisis effect as percentage drop in orders k months after Lehman Brothers

Note: Last column indicates after how many months the effect has vanished (= 0).

Figure 7 summarizes estimated crisis effect and scrappage subsidy effect. The left column of diagrams plots the log of domestic vehicle orders along with fitted values (upper panel) and the estimated crisis effect and scrapping bonus effect (lower panel), respectively. The second column analogously refers to orders from abroad.

From Table 3.4 (where first row refers to domestic orders and second row to foreign orders) in combination with Table 3.1, we can see that the automobile industry's reaction to the crisis compared to the crisis effect in other industries is not special. This concerns both the size of the negative effect and the fact that foreign orders were hit more severely than domestic orders. However, we also see that it took domestic orders in the German automobile industry by far the longest to get back on track: overall, a remarkable 41 months. This is a strong indication for the temporary product-specific subsidy having indeed led to structural disruptions that in the end substantially prolonged the impact and aftermath of the crisis through pull-forward effects of car sales.

3.5 Disentangling by estimating counterfactual intervention-free reactions

Strategic pull-forward effect The German scrapping bonus, just like the cash for clunkers program (officially named "Car allowance rebate system" or briefly CARS; see Goolsbee and Krueger, 2015) in the United States that the U.S. federal government started coinciding with the phase-out of the German program, induced sales of additional cars in the short run. However, it might have led to a substantial reversal in the sense of households "front-loading" their expenditures for vehicles in the medium run (Mian and Sufi, 2012). It is straightforward to suppose that consumers who had planned to buy a new car in 2010 or later anyway pulled forward their purchases of new vehicles due to the subsidy.[10] This in turn could have led to a situation in which vehicle orders (and purchases) did not normalize after the end of the scrapping bonus or of the

[10] This is closely linked to a "free-rider" problem, which we describe in more detail later.

crisis. We may test this by using a model specification that differs from the one used hitherto. Basically, the idea is to test two different specifications for m_t against each other. The first one just as the preceding ones assumes that vehicle orders got back on track after the subsidy and/or the crisis had ended, i.e., that there was no permanent shift in the mean of the series. The second possible specification presumes that orders remained on a new, lower level after 2009. In this case, the first part of equation (3.6) has the following form

$$\left[\frac{\omega_0}{1-\delta_1 L} + \frac{\omega_1}{1-\delta_{1a} L}\right] \eta_{t,1}^{(\tau_1,\tau_2)},$$

where $\delta_{1a} = 1$, i.e. the shift in the series mean is modeled as

$$m_t = \left[\frac{\omega_0}{1-\delta_1 L} + \frac{\omega_1}{1-L}\right] \eta_{t,1}^{(\tau_1,\tau_2)} + \frac{\omega_2}{1-\delta_2 L} \eta_{t,2}^{(\tau_1,\tau_2)}. \tag{3.7}$$

The estimated effect will then represent stylized reactions as shown in Figure 8.[11]

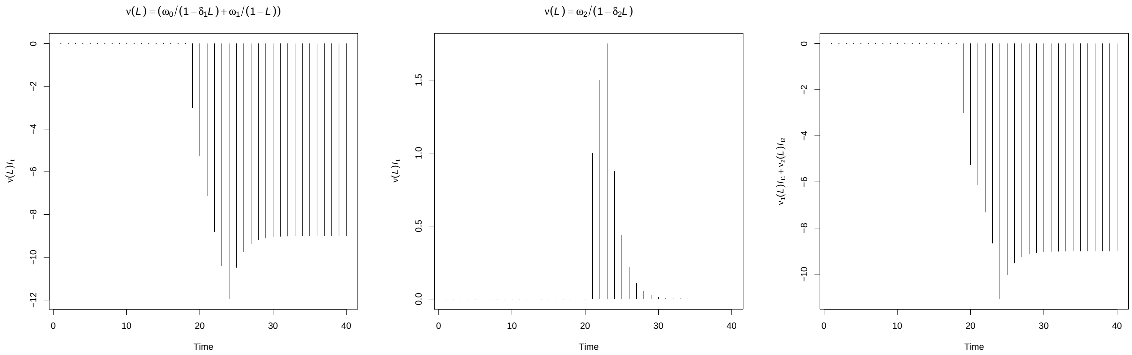
However, if we modify the specification of the transfer function according to (3.7) the resulting estimate for ω_1 is neither economically meaningful nor statistically significant. Furthermore, the AIC value of the new model increases (AIC $= -858.5$). Thus, we conclude that the more parsimonious model is justified.

In line with our intuition, there seems to be no evidence that pull-forward sales by implying structural disruptions in the automobile market have led to a permanent decrease in vehicle orders following the crisis and/or the scrappage program. Nevertheless, "front-loading" of household expenditures on vehicles most probably prevented the German automobile industry to recover as fast as other industries did.[12] As initially suspected, it actually led to a transitory decrease of vehicle orders following the end of the scrapping bonus; see Table 3.4. In what follows, we compute and visualize this externality by estimating the net effect of the scrappage scheme.

[11]Note, the crisis effect in the pharmaceutical industry has already been modeled in this way.

[12]Microeconomically, one route of reasoning for the substantially delayed rebound of consumer demand for autos might be that some households planned the acquisition of two low price-segment products for 2010 or later and due to the subsidy not only pulled forward their purchasing but also changed their plan to acquire only one (subsidized) product from the premium price-segment. However, this contrasts with international experience suggesting a boost of low-margin segments (OECD, 2010) and our volume index series does not allow to test such hypotheses.

Figure 8: Transfer function specification for a permanent drop in vehicle orders

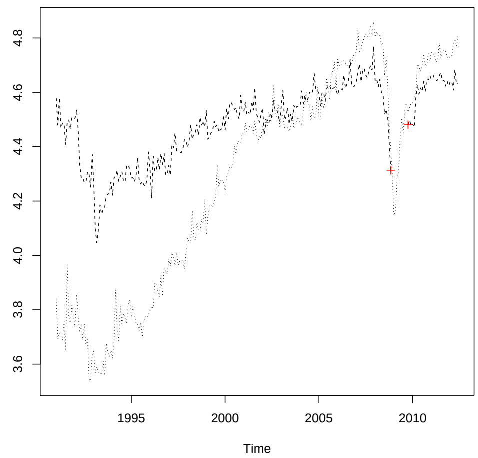


Unintentional windfall-profit effect In the following, we seek to calculate the hypothetical crisis effect in the absence of a scrapping subsidy in order to quantify a potential and frequently debated on free-rider effect of such bonus-measures. The idea is to address the question of how many cars would have been ordered (counterfactually) between January and September 2009 if there had been no subsidizing program. Thus, the aim is to assess the ineffective part of the scrappage scheme by also accounting for the fact that vehicle orders might have regained over the year after January 2009 even without the installation of the program. This quantitative assessment is done in three steps. First, we assume that the series for domestic vehicle orders was not observed between January and September 2009 (see Figure 9). Secondly, we transform the series for foreign and domestic orders, where the latter is only partially observed, into a state space representation and estimate values for the missing observations by applying the Kalman Filter.[13] Based on the filtered values for the missing observations we then are able to calculate what the crisis impact on the German automobile industry would have been without the scrapping subsidy, i.e. the net effect.

A particular advantage of state-space modeling is its ability to treat time series with missing observations (Jones, 1980). Shumway and Stoffer (2008) describe the necessary modifications to fit multivariate state-space models to data with missing observations.

[13]Thus, the values for the missing observations are estimated using the Kalman Filter by making use of the information incorporated in a second series (foreign orders), which is assumed to be related to the series with missing observations. This method is advocated by Harvey and Chung (2000). A detailed outline is given in the Appendix. Alternatively, one could estimate missing observations based on forecasts of a naïve AR(2) fitted to the data up to 12/2008. However, as shown in the Appendix, our approach relying on Kalman Filter values turns out to be the superior one.

Figure 9: Log orders, missing observations 01/09 to 09/09 for inland orders (dashed)



As a general starting point think of a model as given by equations (A.5.1) and (A.5.2) in the Appendix. Next, suppose that the $n \times 1$ observation vector may be partitioned $\boldsymbol{y}_t = \left[\boldsymbol{y}_t^{(1)'}, \boldsymbol{y}_t^{(2)'}\right]'$ with the first $n_{1t} \times 1$ component being observed and the second $n_{2t} \times 1$ component being unobserved. The partitioned measurement equation then has the form

$$\begin{pmatrix} \boldsymbol{y}_t^{(1)} \\ \boldsymbol{y}_t^{(2)} \end{pmatrix} = \begin{pmatrix} \boldsymbol{Z}_t^{(1)} \\ \boldsymbol{Z}_t^{(2)} \end{pmatrix} \boldsymbol{\alpha}_t + \begin{pmatrix} \boldsymbol{u}_t^{(1)} \\ \boldsymbol{u}_t^{(2)} \end{pmatrix}, \tag{3.8}$$

where $\boldsymbol{Z}_t^{(1)}$ and $\boldsymbol{Z}_t^{(2)}$ are the $n_{1t} \times m$ and $n_{2t} \times m$ partitioned measurement or observation matrices, respectively. In case of missing observations, the covariance matrix of the measurement errors between the observed and the unobserved parts is given by

$$Cov \begin{pmatrix} \boldsymbol{u}_t^{(1)} \\ \boldsymbol{u}_t^{(2)} \end{pmatrix} = \begin{pmatrix} \boldsymbol{H}_{11t} & \boldsymbol{H}_{12t} \\ \boldsymbol{H}_{21t} & \boldsymbol{H}_{22t} \end{pmatrix}. \tag{3.9}$$

The most straightforward way to deal with missing obeservations is to always keep an n-dimensional measurement equation zeroing out certain components. In case of missing observations at time t we just have to substitute $\boldsymbol{y}_t$, $\boldsymbol{Z}_t$ and $\boldsymbol{H}_t$ in the updating equations (A.5.10) and (A.5.11) of the Appendix by

$$\boldsymbol{y}_t = \begin{pmatrix} \boldsymbol{y}_t^{(1)} \\ \boldsymbol{0} \end{pmatrix}, \ \boldsymbol{Z}_t = \begin{pmatrix} \boldsymbol{Z}_t^{(1)} \\ \boldsymbol{0} \end{pmatrix}, \ \text{and } \boldsymbol{H}_t = \begin{pmatrix} \boldsymbol{H}_{11t} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I}_{22t} \end{pmatrix}, \tag{3.10}$$

where $\boldsymbol{I}_{22t}$ is the $n_{1t} \times n_{2t}$ identity matrix. Given these substitutions the prediction errors in (A.5.8) and their MSE matrix (A.5.9) in the Appendix will look as follows

$$\boldsymbol{e}_t = \begin{pmatrix} \boldsymbol{e}_t^{(1)} \\ \boldsymbol{0} \end{pmatrix}, \text{ and } \boldsymbol{F}_t = \begin{pmatrix} \boldsymbol{Z}_t^{(1)} \boldsymbol{P}_{t|t-1} \boldsymbol{Z}_t^{(1)'} + \boldsymbol{H}_t & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I}_{22t} \end{pmatrix}. \tag{3.11}$$

Hence, given the substitutions described above the ML-estimation of the state-space model via the prediction error decomposition of the log-likelihood can proceed in the same way as for the complete data case. ML-estimation of the model parameters evolves according to the expectation maximization (EM) algorithm by Shumway and Stoffer (2008). See the Appendix for further detail on ML-based estimation of our state-space models. Figure 10 shows the domestic (left panel) and foreign (right panel) orders of German vehicles as black points. Additionally, also the Kalman Filter values (blue crosses) and the Kalman Smoother values (grey line) together with $\pm 2\sqrt{\boldsymbol{P}_t^{(S)}}$ error bands (dashed red lines) are plotted.[14]

Figure 10: Log domestic and foreign vehicle orders (black points) along with Kalman Filter values (blue crosses), Kalman Smoother values (grey line) and error bands (red)

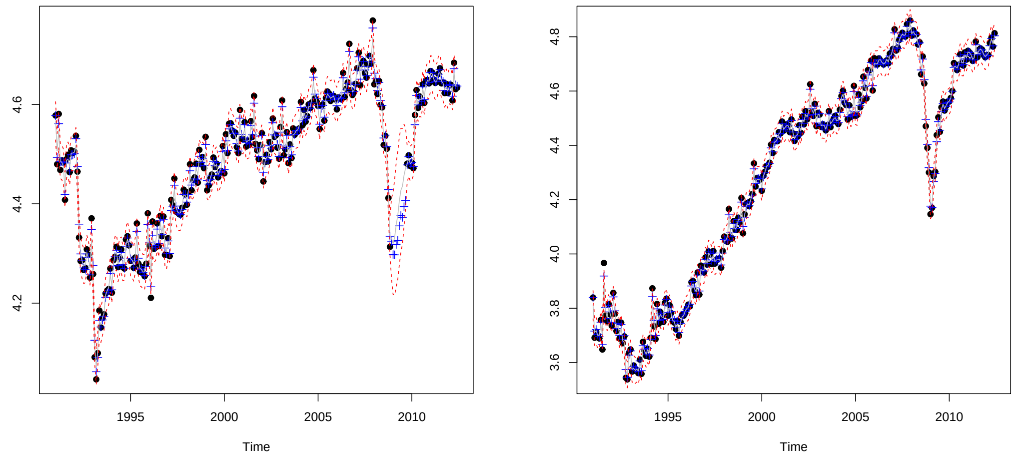
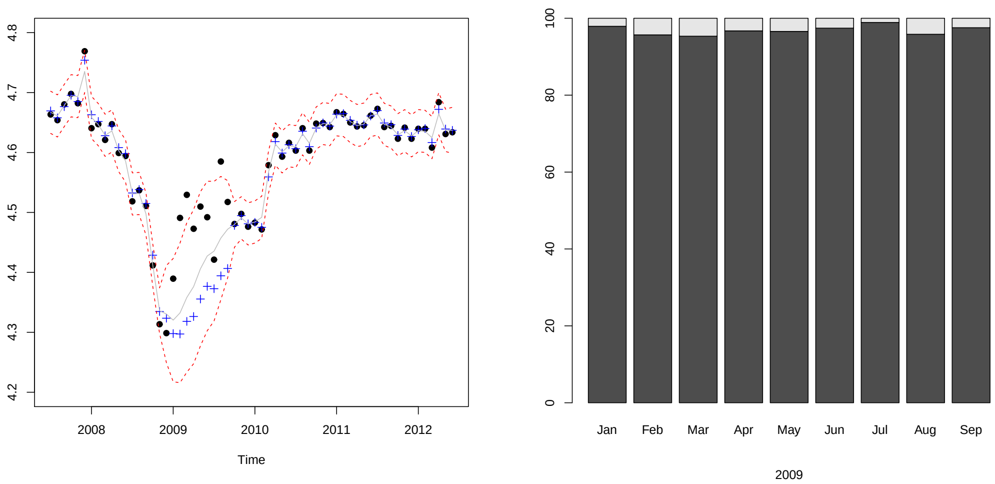


Figure 11 zooms into the left panel of Figure 10 and also shows the estimated free-rider effect (black bars) as percentage share of domestic vehicle orders between 01/2009 and 09/2009. The mean value for the free-rider effect over time is 96.88% of domestic

[14]The superscript $(\cdot)^{(S)}$ denotes Kalman Smoother values. Stoffer (1982) shows how to calculate the values for the Kalman Smoother once the filtered values have been obtained from the missing data specification.

vehicle sales during the existence of the program. Thus, the program actually "created" additional purchases of domestic cars amounting to about 3.12% of observed sales figures during the transitory subsidization period. This figure has to be seen against the backdrop of the fact that under the German scrapping scheme –similar as under the U.S. CARS program– roughly 60 percent of subsidized purchases were foreign brands (Schweinfurth, 2009, p. 4).

Figure 11: Zoom into left panel of Figure 10 and estimated "free-rider" effect (black) as percentage share of domestic vehicle orders: 01/2009 to 09/2009



Note: The ineffective part of the scrapping bonus ("free-rider" effect) is calculated based on Kalman Filter values.

The estimated net effect of the scrapping subsidy is plotted in Figure 12. The red part is the estimated negative net effect of the scrapping bonus resulting from a prolongation of the crisis effect due to structural disruptions in the automobile industry.[15] "Front-loading" of vehicle expenditures (and possibly also by subsidy induced preference bias within the auto-sector model-segments) implied a large proportion of acquired new cars and in turn to a decrease in orders, production, and sales of new cars after the end of the scrapping bonus. Adda and Cooper (2000) have estimated a remarkably similar effect on expected aggregate vehicle sales following the scrapping bonuses introduced by French politicians Éduard Balladure and Alain Juppé in 1994/95 in France. Their findings for the policy effect on vehicle sales, which result from the simulation of a dynamic stochastic discrete choice model, look similar to our estimated net effect of

[15]Without the scrapping bonus domestic orders would have been back to normal after 28 months and not 41 months as it actually took.

the scrapping bonus in Germany. This especially applies to the part associated with the negative effect of the bonus on vehicle sales after the end of the policy, i.e., the red part in the left schedule of Figure 12 (corresponding figures for the other affected manufacturing sector industries are given in Appendix A.6). Thus, based on prior research political decision-makers in Germany could have foreseen, at least, in parts this negative externality of the scrapping bonus.

Substitution effect There is one potential drawback of a temporary product-specific bonus that we have not yet assessed and that is the intersectoral substitution effect. Due to the scrappage scheme demand in, at least, some of the German industries might have been redirected into the automobile sector. For these industries the subsidy should have a negative effect on top of the negative crisis effect. In terms of Figure 2 of Section 1 this is represented by the vertical distance between points A and B. Thus, we seek to test whether the scrapping subsidy, besides the crisis, had an additionally negative effect due to shifting demand between sectors and to quantify this effect (also) for the remaining affected industries of the manufacturing sector. For this purpose we calculate the net effect of the subsidy again. This is done according to the following steps. First, a new intervention model, which now also accounts for the scrapping bonus effect, is fitted to the series of domestic orders in the other manufacturing industries. Different from intervention models used up to now as summarized in Table A.2 in the Appendix, the shift in the mean of the time series due to the two interventions (crisis and scrapping bonus) here is considered as

$$\frac{\omega_0}{1-\delta_1 L}\eta_{t,1}^{(\tau_1,\tau_2)} + \frac{\omega_1}{1-\delta_2 L}\eta_{t,2}^{(\tau_1,\tau_2)},$$

which is the same specification as for the domestic orders in the automobile industry.[16] Overall, the scrapping bonus seems to have had a significantly negative effect on some of the remaining affected industries. Table 3.5 exemplarily shows estimates for one such affected industry, that is, the chemical industry. The Ljung-Box statistics (calculated for 20 lags) implies a p-value of 0.2187. Thus, the assumption of white noise residuals cannot be rejected.

Results shown in Table 3.5 and Figure 12 are based on re-estimates of the counterfactual scenario treating the scrapping bonus observations, i.e. the ones from 01/2009 to 09/2009, as missing and by replacing them by corresponding Kalman Filter values,

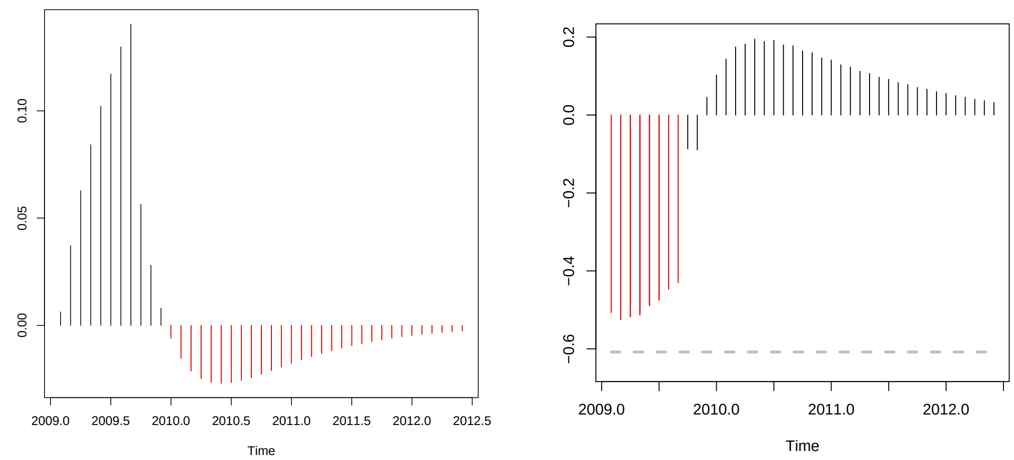
[16]The noise model n_t is not changed.

which are derived from respective bivariate state space models based on domestic and offshore orders. The net effect of the subsidy (in the chemical industry and the remaining industries, respectively) is computed as the difference of the estimated crisis effect based on an intervention model as described above and an intervention model fitted to the series filled up with Kalman Filter values, respectively. Note, the color of bars change indicates the change of regime, i.e. months before and after the program.

θ_1	θ_2	ω_0	δ_1	ω_1	δ_2
-0.2625	0.0909	-0.0365	0.7705	-0.0650	-0.2937
(0.0640)	(0.0762)	(0.0101)	(0.0682)	(0.0161)	(0.1574)
Log-Likelihood = 611.45, AIC = -1210.89					

Table 3.5: Intervention model for logs of inland orders of German chemicals sector. Note: Standard errors given in parantheses.

Figure 12: Distortionary effects of product-specific subsidy on order books



Note: Left panel: automobile sector; right panel: all other manufacturing sectors; period: 01/2009 to 06/2012. The estimated net effect of the subsidy is computed as the difference of the estimated crisis effect based on an intervention model as outlined in Section 3.4.2 and an intervention model fitted to the Kalman Filter values.

For graphical detail on how the different sectors' transfer functions were affected by the temporary scrappage scheme see Figures A.3 to A.5 in the Appendix. In general, there are three stylized reactions of considered industries (apart from the vehicles other than cars industry that we abstract from due to being statistically not significantly affected by the crisis): While the distortionary order book effects in the pharmaceutics, metalworking, chemicals, and electronical and optical devices industries are broadly characterized by a crowding-out with pent-up dynamic demand profile (Figure A.3), the clothing, electronics, and textiles sectors also show indications of crowding-out but without pent-up demand effects in the aftermath of the scrappage scheme (Figure A.4). The closely to the cars sector related machinery industry displays, in terms of size, the strongest increase in orders during and up to two months after the installation of the scrappage scheme (left schedule in Figure A.5). The net transfer function of the paper industry is neither indicative for a crowding-out nor for a crowding-in of demand due to the bonus program (right schedule in Figure A.5).

4 Conclusion

Many countries temporarily subsidize specific products to cushion the effects of overall downturn in economic activity or for meeting the aims of specific lobbying groups. Generally, such measures may boost sales in the short run. However, there might be intersectoral distortions through crowding-out demand for other products as well as intertemporal distortions due to the temporary nature of such programs shifting purchases from the future to the present and possibly reversing the surge in sales after the ending of the measure. The latter is referred to as program reversal or payback effect and cannot be quantified in terms of size and timing relying on standard time series techniques such as sales projections based on error correction models; see, e.g. OECD (2010). In general, the existing literature does not provide a coherent analytical framework to disentangle and quantify intersectoral as well as intertemporal (payback and rebound) distortions and to assess effectiveness of such measures. We propose such a framework based on Kalman Filter/Smoother estimates of counterfactual time series using information contained in series unaffected from the intervention and on netting out corresponding factual and counterfactual response functions.

In our exemplary application, we study the largest car scrappage scheme in recent history installed by the German government between January and September 2009. In contrast to the perception of the scheme having substantially contributed to the stabilization of one of the European core industries, we find the demand-sided effectiveness of such a temporary product-specific subsidy to be rather poor. According to our estimates, the program created additional purchases of domestic products amounting to just about three percent of observed sales figures. Thus, buyers realized substantial unintended windfall gains that are as opposed to implications of alternatives, such as e.g. governmental sales and re-sales on the secondary market, not or less neutral with regard to the public budget. Additionally, stabilization comes according to our estimates at the price of a prolongation of the sectoral trough and a procrastination of the subsequent recovery in the automobile industry by about one year. These are non-trivial costs given that the annual turnover of the automobile industry amounts to ten percent of German GDP. Furthermore, in line with basic theory we find evidence for net sectoral crowding-out and, hence, intersectoral bias of the measure concerning the vast majority of competing industries in the manufacturing sector. It might have been avoided resorting to alternative measures such as consumption vouchers with deadlines. The latter are also less prone to distributive bias, inasmuch they do not discriminate against non-beneficiaries as is the case for households who cannot afford to buy new cars in case of scrappage programs.

In sum, our findings support the recent view of the quantitative theoretical literature that calls the usefulness of national policies to temporarily protect particular domestic industries into question by showing that they also induce technology bias favoring products of dated technology such as diesel engines (Miravete et al., 2018).

References

Adda, J. and R. Cooper, 2000. Balladurette and Juppette: a discrete analysis of scrapping subsidies, *Journal of Political Economy* 108, 778–806.

Angeletos, G.-M. and V. Panousi, 2009. Revisiting the supply side effects of government spending, *Journal of Monetary Economics* 56, 137–153.

Barro, R.J. and C.J. Redlick, 2011. Macroeconomic effects from government purchases and taxes, *Quarterly Journal of Economics* 126, 51–102.

Blanchard, O. and R. Perotti, 2002. An empirical characterization of the dynamic effects of changes in government spending and taxes on output, *Quarterly Journal of Economics* 117, 1329–1368.

Box, G.E.P. and G.C. Tiao, 1975. Intervention analysis with applications to economic and environmental problems, *Journal of the American Statistical Association* 70, 70–79.

De Bondt, G.J., Dieden, H.C., Muzikarova, S., and I. Vincze, 2013. Introducing the ECB indicator on Euro area industrial new orders, European Central Bank Occasional Paper, Nr. 149.

Dempster, A.P., Laird, N.M., and D.B. Rubin, 1977. Maximum likelihood from incomplete data via the EM algorithm, *Journal of the Royal Statistical Society: Series B* 39, 1–38.

Goolsbee, A.D. and A.B. Krueger, 2015. A retrospective look at rescuing and restructuring General Motors and Chrysler, *Journal of Economic Perspectives* 29, 3–24.

Hall, R.E., 2009. By how much does GDP rise if the government buys more output?, *Brookings Papers on Economic Activity* 40, 183–228.

Harris, J.R. and M.P. Todaro, 1970. Migration, unemployment and development: a two-sector analysis, *American Economic Review* 60, 126–142.

Harvey, A. and C.H. Chung, 2000. Estimating the underlying change in unemployment in the UK, *Journal of the Royal Statistical Society: Series A* 163, 303–309.

Jones, R.H., 1980. Maximum likelihood fitting of ARMA models to time series with missing observations, *Technometrics* 22, 389–395.

Leuwer, D. and B. Süssmuth, 2018. The exchange rate susceptibility of European core industries: 1995-2010, *World Economy* 41, 358–392.

Mian, A. and A. Sufi, 2012. The effects of fiscal stimulus: evidence from the 2009 Cash for Clunkers Program, *Quarterly Journal of Economics* 127, 1107–1142.

Miravete, E.J., Moral, M.J., and J. Thurk, 2018. Fuel taxation, emissions policy, and competitive advantage in the diffusion of European diesel automobiles, *RAND Journal of Economics*, forthcoming.

OECD, 2010. The automobile industry in and beyond the crisis, OECD Economic Outlook 86, 87–117.

Petris, G., Petrone, G., and P. Campagnoli, 2009. *Dynamic linear models*, Springer: New York.

Ramey, V.A., 2011. Identifying government spending shocks: it's all in the timing, *Quarterly Journal of Economics* 126, 1–50.

Schiraldi, P., 2011. Automobile replacement: a dynamic structural approach, *RAND Journal of Economics* 42, 266–291.

Schweinfurth, A., 2009. Car-scrapping schemes: an effective economic rescue policy?, Global Subsidies Initiative (GSI) Policy Brief 12/2009, IISD, Geneva.

Schweppe, F., 1965. Evaluation of likelihood functions for Gaussian signals, *IEEE Transactions on Information Theory* 11, 61–70.

Shumway, R.H. and D.S. Stoffer, 2008. An approach to time series smoothing and forecasting using the EM algorithm, *Journal of Time Series Analysis* 3, 253–264.

Shumway, R.H. and D.S. Stoffer, 2011. *Time series analysis and its applications*, Springer: New York.

Stoffer, D.S., 1982. *Estimation of parameters in a linear dynamic system with missing observations*, Ph.D. dissertation, University of California, Davis.

Strulik, H. and T. Trimborn, 2017. The spending multiplier in the medium run, *German Economic Review* 18, 154–181.

Appendix

A.1 Model motivating Figure 2

Let the model economy consist of a sector x and all remaining industries y, where sector x is subsidized. The two divisions produce with production functions

$$x = f(R_x); \quad f' > 0,\, f'' < 0 \tag{A.1.1}$$
$$y = g(R_y); \quad g' > 0,\, g'' < 0, \tag{A.1.2}$$

where R denotes resources of any kind. In equilibrium the following three conditions need to hold

$$(p+s)f'(R_x) = m_x^0 \tag{A.1.3}$$
$$g'(R_y) = m_y \tag{A.1.4}$$
$$m_y - c = \pi m_x^0 + (1-\pi)\alpha, \tag{A.1.5}$$

i.e. input factors in y (for which the price is normalized to unity) are rewarded their marginal product m. The same applies for sector x; however, market price p is upwardly biased by a (scrappage) subsidy amounting to s. In equation (A.1.5) c are costs of any kind due to resources shifting from one part of the economy to another, π is the probability of resources being used for production in sector x, α is the alternative use value of resources spent in sector x. Equation (A.1.5) ensures that in equilibrium there is no flow of resources from all other sectors y into x and vice versa. π is given by

$$\pi = \frac{R_x}{R_0 - R_y}, \tag{A.1.6}$$

where R_0 is the total amount of resources in the model economy. Obviously, if $\pi < 1$ there are some resources unused. By simple logics, we can already say that in case the subsidization of sector x ends, R_x should decrease. As π decreases

$$m_y - c > \pi m_x^0 + (1-\pi)\alpha, \tag{A.1.7}$$

mobile resources are drawn from sector x into remaining sectors y. As a consequence m_y will have to decrease in order for the economy to reach a new equilibrium.

In the following we will briefly consider the effects of a variation in s. What are the social effects of a variation of s? Social benefits are given by

$$V = pf(R_x) + g(R_y) - k(R_y - R_y^0). \tag{A.1.8}$$

The subtractive part in (A.1.8) represents adjustment costs that are due to sectorally shifting resources. These costs represent social costs of any kind. Hence, the (gross) effect of a variation in s is given by

$$\frac{dV}{ds} = pf'\frac{dR_x}{ds} + \underbrace{(g' - k')}_{>0}\frac{dR_y}{ds}. \tag{A.1.9}$$

In order to isolate the effects of a variation in s we need to quantify dR_x/ds and dR_y/ds first. Thus, we need to consider all three equilibrium conditions. For the first condition, we obtain

$$(p+s)f''dR_x + f'ds = 0 \quad \Rightarrow \quad \frac{dR_x}{ds} = -\frac{f'}{(p+s)f''} = \beta > 0. \tag{A.1.10}$$

It is slightly more complicated to calculate dR_y/ds. First, it requires the total derivative of the second equilibrium condition, which is simply given by

$$g''dR_y = dm_y. \tag{A.1.11}$$

Secondly, considering the total derivative of the third equilibrium condition implies

$$dm_y = (m_y^0 - \alpha)d\pi = \delta_x d\pi. \tag{A.1.12}$$

Substituting (A.1.12) into (A.1.11), we are given

$$g''dR_y = \delta_x d\pi. \tag{A.1.13}$$

From (A.1.6) we see that

$$\begin{aligned} d\pi &= \frac{(R_0 - R_y)dR_x - R_x(-dR_y)}{(R_0 - R_y)^2} = \frac{(R_0 - R_y)dR_x + R_x dR_y}{(R_0 - R_y)^2} \\ &= \frac{dR_x}{R_0 - R_y} + \frac{R_x}{R_0 - R_y} \cdot \frac{dR_y}{R_0 - R_y} = \frac{dR_x}{R_0 - R_y} + \frac{\pi dR_y}{R_0 - R_y}. \end{aligned} \tag{A.1.14}$$

Combining (A.1.13) and (A.1.12) results in

$$\begin{aligned} g''dR_y &= \delta_x \frac{dR_x}{R_0 - R_y} + \delta_x \frac{\pi dR_y}{R_0 - R_y} \quad \Leftrightarrow \\ \left(g'' - \delta_x \frac{\pi}{R_0 - R_y}\right) dR_y &= \frac{\delta_x}{R_0 - R_y} dR_x \end{aligned} \tag{A.1.15}$$

Relationship (A.1.10) allows to substitute dR_x by βds and, hence,

$$dR_y = \frac{\delta_x \beta ds}{\left(g'' - \frac{\delta_x \pi}{R_0 - R_y}\right)(R_0 - R_y)} \quad \Rightarrow \quad \frac{dR_y}{ds} = \gamma < 0 \tag{A.1.16}$$

We now know the respective signs of dR_x/ds and dR_y/ds. Thus, based on equation (A.1.9), it can be stated that in case s is decreased resources (and thus output) in sector x will decrease. However, this may, at least partly, be compensated by resources drawn into and output produced in sector y. If the first additive part of (A.1.9) is larger than the second one there will be inefficiency in the sense of unused resources.

These qualitative results are summarized graphically in Figure 2 in the text.

A.2 Coding of variables and descriptive statistics

Industry	Industry No.	Series	Series Name	Min	Max	Mean	Sd
Electronical and optical devices	1	orders inl(and)	OIElinl	54.20	173.20	95.30	33.38
		orders for(eign)	OIElfor	33.70	166.90	79.16	35.06
Clothing	2	orders inl	OIClinl	57.10	241.70	122.62	41.85
		orders for	OIClfor	71.10	173.90	98.42	16.88
Chemicals	3	orders inl	OIChinl	77.40	109.30	97.81	5.30
		orders for	OIChfor	58.20	115.80	85.11	14.75
Electronics	4	orders inl	OIEdinl	75.00	141.00	99.67	8.73
		orders for	OIEdfor	43.90	145.00	84.35	24.54
Cars	5	orders inl	OICainl	57.20	117.80	89.59	12.07
		orders for	OICafor	34.40	129.00	78.15	28.45
Metalworking	6	orders inl	OIMeinl	81.00	122.30	99.86	9.25
		orders for	OIMefor	44.90	139.60	82.15	25.70
Production of paper	7	orders inl	OIPainl	86.20	112.20	97.97	6.34
		orders for	OIPafor	47.10	118.10	83.84	21.04
Pharmaceutics	8	orders inl	OIPhinl	71.40	117.40	89.03	8.45
		orders for	OIPhfor	28.60	130.90	77.52	28.60
Textiles	9	orders inl	OITxinl	73.20	221.40	126.93	36.08
		orders for	OITxfor	75.50	109.10	94.59	7.79
Machines	10	orders inl	OIMainl	65.70	131.70	97.85	11.84
		orders for	OIMafor	50.40	143.70	84.58	25.05
Production of metal	11	orders inl	OIStinl	59.40	148.70	102.33	11.03
		orders for	OIStfor	54.90	120.20	85.87	15.33
Vehicles other than cars	12	orders inl	OIBoinl	42.10	508.10	88.55	45.94
		orders for	OIBofor	12.30	294.10	74.89	48.88

Table A.1: Coding of variables and descriptive statistics.

A.3 Overview of intervention models

Industry No.	Series	n_t	m_t	p-val. Ljung-Box stat.
1	inl(and)	ARIMA(0,1,1)	$(\frac{\omega_0}{1-\delta_1 L-\delta_2 L^2})\eta_t^{(\tau_1,\tau_2)}$	0.7779
	for(eign)	ARIMA(0,1,1)	$(\frac{\omega_0}{1-\delta_1 L})\eta_t^{(\tau_1,\tau_2)}$	0.4156
2	inl	ARIMA(2,1,2)	$(\frac{\omega_0}{1-\delta_1 L})L^2\zeta_t^{\tau}$	0.2823
	for	ARIMA(4,1,2)	$(\frac{\omega_0}{1-\delta_1 L})L^2\zeta_t^{\tau}$	0.7021
3	inl	ARIMA(0,1,2)	$(\frac{\omega_0}{1-\delta_1 L})\eta_t^{(\tau_1,\tau_2)}$	0.1209
	for	ARIMA(2,1,2)	$(\frac{\omega_0}{1-\delta_1 L})\eta_t^{(\tau_1,\tau_2)}$	0.0516
4	inl	ARIMA(2,1,1)	$(\frac{\omega_0}{1-\delta_1 L})\eta_t^{(\tau_1,\tau_2)}$	2.46e-05
	for	ARIMA(2,1,2)	$(\frac{\omega_0}{1-\delta_1 L-\delta_2 L^2})\eta_t^{(\tau_1,\tau_2)}$	0.2973
5			See section 3.4	
6	inl	ARIMA(2,1,1)	$(\frac{\omega_0}{1-\delta_1 L})\eta_t^{(\tau_1,\tau_2)}$	0.1581
	for	ARIMA(1,1,1)	$(\frac{\omega_0}{1-\delta_1 L})\eta_t^{(\tau_1,\tau_2)}$	0.8511
7	inl	ARIMA(2,1,0)	$(\frac{\omega_0}{1-\delta_1 L})\eta_t^{(\tau_1,\tau_2)}$	0.8510
	for	ARIMA(0,1,1)	$(\frac{\omega_0}{1-\delta_1 L})\eta_t^{(\tau_1,\tau_2)}$	0.2647
8	inl	ARIMA(2,1,0)	$(\omega_0 + \frac{\omega_1}{1-\delta_1 L})\zeta_t^{\tau}$	0.7869
	for	ARIMA(2,1,3)	-	0.1998
9	inl	ARIMA(2,1,0)	$(\frac{\omega_0}{1-\delta_1 L-\delta_2 L^2})\eta_t^{(\tau_1,\tau_2)}$	0.7107
	for	ARIMA(2,1,2)	$(\frac{\omega_0}{1-\delta_1 L})\zeta_t^{\tau}$	0.0726
10	inl	ARIMA(2,1,2)	$(\omega_0 + \frac{\omega_1}{1-\delta_1 L})\eta_t^{(\tau_1,\tau_2)}$	0.5617
	for	ARIMA(2,1,0)	$(\frac{\omega_0}{1-\delta_1 L})\eta_t^{(\tau_1,\tau_2)}$	0.7977
11	inl	ARIMA(3,1,3)	$(\frac{\omega_0}{1-\delta_1 L})\eta_t^{(\tau_1,\tau_2)}$	0.1783
	for	ARIMA(2,1,0)	$(\frac{\omega_0}{1-\delta_1 L})\eta_t^{(\tau_1,\tau_2)}$	0.1350
12	inl	ARIMA(2,1,2)	-	0.0990
	for	ARIMA(4,1,1)	-	0.1843

Table A.2: Intervention models fitted to log series. Ljung-Box statistic is calculated based on 20 lags.

A.4 Estimating the crisis and scrapping bonus effect on domestic orders – alternative specification for m_t

Note, that the transfer function m_t could also be specified in the following way

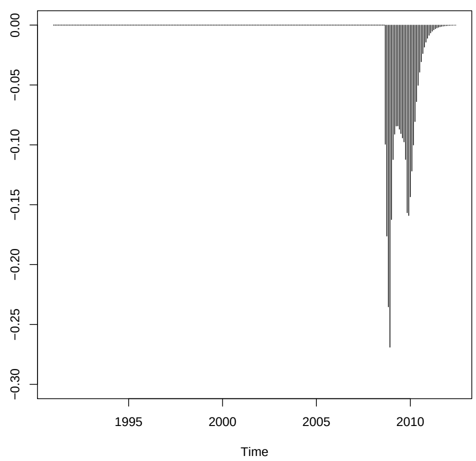
$$m_t = \frac{\omega_0}{1-\delta_1 L}\eta_{t,1}^{(\tau_1,\tau_2)} + \left[\omega_1 + \frac{\omega_2}{1-\delta_2 L}\right]\eta_{t,2}^{(\tau_1,\tau_2)}. \tag{A.4.1}$$

Table A.3 shows the ML estimates of the respective intervention model. As we can see all coefficient estimates are significant. The AIC is even lower than in case of the model specification in section 3.4.2. The Ljung-Box statistic (calculated for 20 lags) has a p-value = 0.5610. However, the sign of ω_1 does not seem to be economically meaningful, which is why we stick to the more parsimonious specification of m_t (anyway, results do not change qualitatively).

ϕ_1	ϕ_2	ω_0	δ_1	ω_1	ω_2	δ_2
-0.4398	-0.1937	0.7708	-0.0995	-0.2482	0.2601	0.5448
(0.0620)	(0.0632)	(0.0201)	(0.0573)	(0.1070)	(0.0909)	(0.1143)
Log-Likelihood = 440.19, AIC = −866.38						

Table A.3: ML-estimates of intervention model fitted to logs of inland orders in the German automobile industry – alternative specification for m_t.

Figure A.1: Estimated crisis and bonus effect: alternative specification of m_t.



A.5 State-space models, Kalman Filter, and model estimation

A.5.1 State-space models

A state space-model for an n-dimensional time series $\boldsymbol{y}_t$ consist of a measurement equation that relates the observed data to an m-dimensional state vector $\boldsymbol{\alpha}_t$. The generation of the state vector $\boldsymbol{\alpha}_t$ from the past state $\boldsymbol{\alpha}_{t-1}$, for $t = 1, ..., T$, is determined by the state equation. The measurement equation has the form

$$\boldsymbol{y}_t = \boldsymbol{Z}_t\boldsymbol{\alpha}_t + \boldsymbol{d}_t + \boldsymbol{u}_t, \quad t = 1, ..., T. \tag{A.5.1}$$

In A.5.1 $\boldsymbol{Z}_t$ is an $n \times m$ matrix called measurement or observation matrix, $\boldsymbol{d}_t$ is an $n \times 1$ vector and $\boldsymbol{u}_t \sim$ iid $N(\mathbf{0}, \boldsymbol{H}_t)$ is an error vector. The state equation is given by

$$\boldsymbol{\alpha}_t = \boldsymbol{T}_t\boldsymbol{\alpha}_{t-1} + \boldsymbol{c}_t + \boldsymbol{R}_t\boldsymbol{\nu}_t, \quad t = 1, ..., T. \tag{A.5.2}$$

In A.5.2 $\boldsymbol{T}_t$ is an $m \times m$ matrix called transition matrix, $\boldsymbol{c}_t$ is an $m \times 1$ vector, $\boldsymbol{R}_t$ is an $m \times g$ matrix and $\boldsymbol{\nu}_t \sim$ iid $N(\mathbf{0}, \boldsymbol{Q}_t)$ is a $g \times 1$ error vector. The matrices $\boldsymbol{Z}_t$, $\boldsymbol{d}_t$, $\boldsymbol{H}_t$, $\boldsymbol{T}_t$, $\boldsymbol{c}_t$, $\boldsymbol{R}_t$ and $\boldsymbol{Q}_t$ are called system matrices. It is frequently assumed that the errors of the measurement and the transition equation are uncorrelated, i.e.

$$E[\boldsymbol{u}_t\boldsymbol{\nu}_t'] = \mathbf{0} \quad \forall s, t = 1, ..., T.$$

However, this assumption is not necessary; see Shumway and Stoffer (2011, p. 354-358) for a discussion of the case of correlated errors. Furthermore, it is assumed that the initial state is given by a normal vector

$$\boldsymbol{\alpha}_0 \sim N(\boldsymbol{a}_0, \boldsymbol{P}_0); \quad E[\boldsymbol{u}_t\boldsymbol{a}_0'] = \mathbf{0},\ E[\boldsymbol{\nu}_t\boldsymbol{a}_0'] = 0, \quad t = 1, ..., T.$$

Note, that the model given in A.5.2 which includes only one lag is not at all restrictive as processes with higher orders may be casted into a state space representation as well. Think for example of an AR(2)-process

$$y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \nu_t, \quad \text{with } \nu_t \sim \text{iid } N(0, \sigma^2).$$

If we define $\boldsymbol{\alpha}_t := [y_t, y_{t-1}]'$ the transition equation becomes

$$\begin{pmatrix} y_t \\ y_{t-1} \end{pmatrix} = \begin{pmatrix} \phi_1 & \phi_2 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} y_{t-1} \\ y_{t-2} \end{pmatrix} + \begin{pmatrix} \phi_0 \\ 0 \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \end{pmatrix} \nu_t,$$

whereas the measurement equation would be

$$y_t = [1, 0]\boldsymbol{\alpha}_t.$$

Thus, the system matrices are

$$\boldsymbol{T} = \begin{pmatrix} \phi_1 & \phi_2 \\ 1 & 0 \end{pmatrix},\ \boldsymbol{R} = \begin{pmatrix} 1 \\ 0 \end{pmatrix},\ \boldsymbol{c} = \begin{pmatrix} \phi_0 \\ 0 \end{pmatrix},\ Q = \sigma^2,\ \boldsymbol{Z}_t = [1, 0],\ d_t = 0,\ u_t = 0 \text{ and}$$

$$H_t = 0.$$

A.5.2 The Kalman Filter procedure

In most cases the aim of any analysis based on a state-space model as defined by equations A.5.1 and A.5.2 will be to produce estimators for the underlying unobserved signal $\boldsymbol{\alpha}_t$ given the data $\boldsymbol{y}_s$, for $s = 1, ..., S$. Whenever $s = t$ this problem is called filtering, while we speak of smoothing if $s > t$ and forecasting in case $s < t$. The problem of finding such estimators is solved by the Kalman Filter, Kalman Smoother and forecasting recursions respectively; see Petris et al. (2009, p. 53-72). In the following we will focus on the derivation of the Kalman Filter (i.e. $s = t$).

The Kalman Filter is a set of recursion equations (prediction equations and updating equations) that determine the optimal estimates for the state vector $\boldsymbol{\alpha}_t$ given the information available at time t (which we denote by I_t). The following definitions are used

$$\boldsymbol{a}_t \coloneqq E[\boldsymbol{\alpha}_t | I_t] \tag{A.5.3}$$

and

$$\boldsymbol{P}_t \coloneqq E[(\boldsymbol{\alpha}_t - \boldsymbol{a}_t)(\boldsymbol{\alpha}_t - \boldsymbol{a}_t)' | I_t]. \tag{A.5.4}$$

I.e. $\boldsymbol{a}_t$ is the optimal estimator of $\boldsymbol{\alpha}_t$ based on I_t and $\boldsymbol{P}_t$ is the MSE matrix of $\boldsymbol{a}_t$.

Prediction equations Given $\boldsymbol{a}_{t-1}$ and $\boldsymbol{P}_{t-1}$ we get

$$\begin{aligned} \boldsymbol{a}_{t|t-1} &= E[\boldsymbol{\alpha}_t | I_{t-1}] \\ &= \boldsymbol{T}_t \boldsymbol{a}_{t-1} + \boldsymbol{c}_t \qquad (A.5.5) \\ \boldsymbol{P}_{t|t-1} &= E[(\boldsymbol{\alpha}_t - \boldsymbol{a}_{t-1})(\boldsymbol{\alpha}_t - \boldsymbol{a}_{t-1})' | I_{t-1}] \\ &= \boldsymbol{T}_t \boldsymbol{P}_{t-1} \boldsymbol{T}_t' + \boldsymbol{R}_t \boldsymbol{Q}_t \boldsymbol{R}_t. \qquad (A.5.6) \end{aligned}$$

The optimal predictor of $\boldsymbol{y}_t$ is then

$$\begin{aligned} \boldsymbol{y}_{t|t-1} &= \boldsymbol{Z}_t \boldsymbol{a}_{t|t-1} + \boldsymbol{d}_t \\ &= \boldsymbol{Z}_t \boldsymbol{T}_t \boldsymbol{a}_{t-1} + \boldsymbol{Z}_t \boldsymbol{c}_t + \boldsymbol{d}_t \\ &= \boldsymbol{Z}_t (\boldsymbol{T}_t \boldsymbol{a}_{t-1} + \boldsymbol{c}_t) + \boldsymbol{d}_t. \end{aligned} \tag{A.5.7}$$

The prediction error and its MSE matrix are then

$$\begin{aligned} \boldsymbol{e}_t &= \boldsymbol{y}_t - \boldsymbol{y}_{t|t-1} \\ &= \boldsymbol{y}_t - \boldsymbol{Z}_t \boldsymbol{a}_{t|t-1} - \boldsymbol{d}_t \\ &= \boldsymbol{Z}_t \boldsymbol{\alpha}_t + \boldsymbol{d}_t + \boldsymbol{u}_t - \boldsymbol{Z}_t \boldsymbol{a}_{t|t-1} - \boldsymbol{d}_t \\ &= \boldsymbol{Z}_t (\boldsymbol{\alpha}_t - \boldsymbol{a}_{t|t-1}) + \boldsymbol{u}_t \end{aligned} \tag{A.5.8}$$

and

$$E[\boldsymbol{e}_t \boldsymbol{e}_t'] \coloneqq \boldsymbol{F}_t = \boldsymbol{Z}_t \boldsymbol{P}_{t|t-1} \boldsymbol{Z}_t' + \boldsymbol{H}_t. \tag{A.5.9}$$

Updating equations In the moment $\boldsymbol{y}_t$ is observed the optimal predictor and its MSE matrix are updated according to

$$\begin{aligned}
\boldsymbol{a}_t &= \boldsymbol{a}_{t|t-1} + \boldsymbol{P}_{t|t-1}\boldsymbol{Z}_t'\boldsymbol{F}_t^{-1}(\boldsymbol{y}_t - \boldsymbol{y}_{t|t-1}) \\
&= \boldsymbol{a}_{t|t-1} + \boldsymbol{P}_{t|t-1}\boldsymbol{Z}_t'\boldsymbol{F}_t^{-1}(\boldsymbol{y}_t - \boldsymbol{Z}_t\boldsymbol{\alpha}_{t|t-1} - \boldsymbol{d}_t) \\
&= \boldsymbol{a}_{t|t-1} + \boldsymbol{P}_{t|t-1}\boldsymbol{Z}_t'\boldsymbol{F}_t^{-1}\boldsymbol{e}_t && \text{(A.5.10)} \\
\boldsymbol{P}_t &= \boldsymbol{P}_{t|t-1} - \underbrace{\boldsymbol{P}_{t|t-1}\boldsymbol{Z}_t\boldsymbol{F}_t^{-1}}_{\text{Kalman Gain}}\boldsymbol{Z}_t\boldsymbol{P}_{t|t-1}. && \text{(A.5.11)}
\end{aligned}$$

Filter derivation The derivation of the Kalman Filter makes use of the following properties of a bivariate normal distribution: Given y the distribution of x is normal with

$$\begin{aligned}
E[x|y] &= \boldsymbol{\mu}_{x|y} = \boldsymbol{\mu}_x + \boldsymbol{\Sigma}_{xy}\boldsymbol{\Sigma}_{yy}^{-1}(\boldsymbol{y} - \boldsymbol{\mu}_y) && \text{(A.5.12)} \\
Var(x|y) &= \boldsymbol{\Sigma}_{xx} - \boldsymbol{\Sigma}_{xy}\boldsymbol{\Sigma}_{yy}^{-1}\boldsymbol{\Sigma}_{yx}. && \text{(A.5.13)}
\end{aligned}$$

For the state vector at time $t = 1$ we get

$$\boldsymbol{\alpha}_1 = \boldsymbol{T}_1\boldsymbol{\alpha}_0 + \boldsymbol{c}_1 + \boldsymbol{R}_1\boldsymbol{\nu}_1,$$

with $\boldsymbol{\alpha}_0 \sim N(\boldsymbol{a}_0, \boldsymbol{P}_0)$, $\boldsymbol{\nu}_1 \sim N(\boldsymbol{0}, \boldsymbol{Q}_1)$ and $E[\boldsymbol{\alpha}_0\boldsymbol{\nu}_1'] = \boldsymbol{0}$. In a linear Gaussian state-space model the initial state vector is normally distributed with

$$\begin{aligned}
\boldsymbol{a}_{1|0} &:= E[\boldsymbol{\alpha}_1] = \boldsymbol{T}_1\boldsymbol{a}_0 + \boldsymbol{c}_1 && \text{(A.5.14)} \\
\boldsymbol{P}_{1|0} &:= Var(\boldsymbol{\alpha}_1) = \boldsymbol{T}_1\boldsymbol{P}_{1|0}\boldsymbol{T}_1' + \boldsymbol{R}_1\boldsymbol{Q}_1\boldsymbol{R}_1'.
\end{aligned}$$

From the measurement equation we get

$$\boldsymbol{y}_1 = \boldsymbol{Z}_1\boldsymbol{\alpha}_1 + \boldsymbol{d}_1 + \boldsymbol{u}_1,$$

with $\boldsymbol{u}_1 \sim N(\boldsymbol{0}, \boldsymbol{H}_1)$ such that

$$\begin{aligned}
\boldsymbol{y}_{1|0} &:= E[\boldsymbol{y}_1] = \boldsymbol{Z}_1\boldsymbol{a}_{1|0} + \boldsymbol{d}_1 && \text{(A.5.15)} \\
Var(\boldsymbol{y}_1) &= E[(\boldsymbol{y}_1 - \boldsymbol{y}_{1|0})(\boldsymbol{y}_1 - \boldsymbol{y}_{1|0})'] \\
&= E[(\boldsymbol{Z}_1\{\boldsymbol{\alpha}_1 - \boldsymbol{a}_{1|0}\} + \boldsymbol{u}_1)(\boldsymbol{Z}_1\{\boldsymbol{\alpha}_1 - \boldsymbol{a}_{1|0}\} + \boldsymbol{u}_1)'] \\
&= \boldsymbol{Z}_1\boldsymbol{P}_{1|0}\boldsymbol{Z}_1' + \boldsymbol{H}_1.
\end{aligned}$$

Equations A.5.14 and A.5.15 are the predictions equations for $\boldsymbol{\alpha}_1$ and $\boldsymbol{y}_1$ at $t = 0$. In a next step one has to find the distribution of $\boldsymbol{\alpha}_1$ conditional on $\boldsymbol{y}_1$ being observed (updating). For this purpose the joint normal distribution of $(\boldsymbol{\alpha}_1', \boldsymbol{y}_1')$ must be determined. In finding the joint normal distribution we use

$$\begin{aligned}
\boldsymbol{\alpha}_1 &= \boldsymbol{a}_{1|0} + (\boldsymbol{\alpha}_1 - \boldsymbol{a}_{1|0}) \\
\boldsymbol{y}_1 &= \boldsymbol{y}_{1|0} + \boldsymbol{y}_1 - \boldsymbol{y}_{1|0} \\
&= \boldsymbol{Z}_1\boldsymbol{a}_{1|0} + \boldsymbol{d}_1 + \boldsymbol{Z}_1(\boldsymbol{\alpha}_1 - \boldsymbol{a}_{1|0}) + \boldsymbol{u}_1.
\end{aligned}$$

Note that

$$\begin{aligned}
Cov(\boldsymbol{\alpha}_1, \boldsymbol{y}_1) &= E[(\boldsymbol{\alpha}_1 - \boldsymbol{a}_{1|0})(\boldsymbol{y}_1 - \boldsymbol{y}_{1|0})'] \\
&= E[(\boldsymbol{\alpha}_1 - \boldsymbol{a}_{1|0})(\boldsymbol{Z}_1\{\boldsymbol{\alpha}_1 - \boldsymbol{a}_{1|0}\} + \boldsymbol{u}_1)'] \\
&= E[(\boldsymbol{\alpha}_1 - \boldsymbol{a}_{1|0})(\{\boldsymbol{\alpha}_1 - \boldsymbol{a}_{1|0}\}\boldsymbol{Z}_1' + \boldsymbol{u}_1')] \\
&= E[(\boldsymbol{\alpha}_1 - \boldsymbol{a}_{1|0})(\boldsymbol{\alpha}_1 - \boldsymbol{a}_{1|0})\boldsymbol{Z}_1'] + E[(\boldsymbol{\alpha}_1 - \boldsymbol{a}_{1|0})\boldsymbol{u}_1'] \\
&= \boldsymbol{P}_{1|0}\boldsymbol{Z}_1'.
\end{aligned}$$

Therefore, we get

$$\begin{pmatrix} \boldsymbol{\alpha}_1 \\ \boldsymbol{y}_1 \end{pmatrix} \sim N\left(\begin{pmatrix} \boldsymbol{a}_{1|0} \\ \boldsymbol{Z}_1\boldsymbol{a}_{1|0} + \boldsymbol{d}_1 \end{pmatrix}, \begin{pmatrix} \boldsymbol{P}_{1|0} & \boldsymbol{P}_{1|0}\boldsymbol{Z}_1' \\ \boldsymbol{Z}_1\boldsymbol{P}_{1|0} & \boldsymbol{Z}_1\boldsymbol{P}_{1|0}\boldsymbol{Z}_1' + \boldsymbol{H}_1 \end{pmatrix}\right).$$

Now, together with A.5.12 and A.5.13 we get $(\boldsymbol{\alpha}_1|\boldsymbol{y}_1) \sim N(\boldsymbol{a}_1, \boldsymbol{P}_1)$ with

$$\begin{aligned}
\boldsymbol{a}_1 &= \boldsymbol{a}_{1|0} + \boldsymbol{P}_{1|0}\boldsymbol{Z}_1'(\boldsymbol{Z}_1\boldsymbol{P}_{1|0}\boldsymbol{Z}_1' + \boldsymbol{H}_1)^{-1}(\boldsymbol{y}_1 - \boldsymbol{Z}_1\boldsymbol{a}_{1|0} - \boldsymbol{d}_1) \\
&= \boldsymbol{a}_{1|0} + \boldsymbol{P}_{1|0}\boldsymbol{Z}_1'\boldsymbol{F}_1^{-1}\boldsymbol{e}_1 \qquad \text{(A.5.16)} \\
\boldsymbol{P}_1 &= \boldsymbol{P}_{1|0} - \boldsymbol{P}_{1|0}\boldsymbol{Z}_1'(\boldsymbol{Z}_1\boldsymbol{P}_{1|0}\boldsymbol{Z}_1' + \boldsymbol{H}_1)^{-1}\boldsymbol{Z}_1\boldsymbol{P}_{1|0} \\
&= \boldsymbol{P}_{1|0} - \boldsymbol{P}_{1|0}\boldsymbol{Z}_1'\boldsymbol{F}_1^{-1}\boldsymbol{Z}_1\boldsymbol{P}_{1|0}. \qquad \text{(A.5.17)}
\end{aligned}$$

Note, that A.5.16 and A.5.17 are the Kalman Filter updating equations for $t = 1$.

A.5.3 Maximum Likelihood estimation of state-space models

Let $\boldsymbol{\theta}$ denote the parameters of the state-space model. Note, that these parameters are embodied in the system matrices. The likelihood of the state-space model is calculated based on the prediction errors $\boldsymbol{e}_t$, with $t = 1, ..., T$. It was Schweppe (1965), who first gave the innovations form of the likelihood function. The prediction error decomposition of the (negative) log-likelihood looks as follows

$$-2 \ln L(\boldsymbol{\theta}|\boldsymbol{y}) = nT \ln(2\pi) + \sum_{t=1}^{T} \ln |\boldsymbol{F}_t(\boldsymbol{\theta})| + \sum_{t=1}^{T} \boldsymbol{e}_t'(\boldsymbol{\theta})\boldsymbol{F}_t^{-1}(\boldsymbol{\theta})\boldsymbol{e}_t(\boldsymbol{\theta}). \qquad \text{(A.5.18)}$$

One way to estimate the unknown parameters would be to apply a Newton-Raphson algorithm. Performing a Newton-Raphson estimation evolves according to the following steps:

1. Find some initial values for the parameters: $\boldsymbol{\theta}^{(0)}$,
2. run the Kalman Filter based on $\boldsymbol{\theta}^{(0)}$ to obtain $\left\{\boldsymbol{e}_t^{(0)}\right\}_{t=1}^{T}$ and $\left\{\boldsymbol{F}_t^{(0)}\right\}_{t=1}^{T}$,
3. run one iteration of the Newton-Raphson algorithm with the negative log likelihood as the criterion function to obtain $\boldsymbol{\theta}^{(1)}$,

4. at iteration $j = 1, 2, ...$ repeat steps 2. and 3. based on the respective parameter values as well as predictions errors and MSE matrices thereof. Stop if the parameters or the likelihood stabilize, i.e. when they differ from their predecessor by some predetermined, small amount κ.

Of course, A.5.18 will be a highly nonlinear and complicated function of $\boldsymbol{\theta}$. Thus, it might be difficult to ensure that the Newton-Raphson algorithm does not get stuck in a local minima of the log likelihood function.

Apart from the Newton-Raphson algorithm Shumway and Stoffer (2008) present a procedure, which is based on the EM algorithm of Dempster et al. (1977) and is conceptually simpler. The basic idea of this approach is that if we could observe all the states $\boldsymbol{\alpha}_T = \{\boldsymbol{\alpha}_t\}_{t=0}^T$ together with the observations $\boldsymbol{y}_T = \{\boldsymbol{y}_t\}_{t=1}^T$ we could consider the complete data $\{\boldsymbol{\alpha}_T, \boldsymbol{y}_T\}$. The complete data likelihood could then be written as

$$\begin{aligned}
-2 \ln L(\boldsymbol{\theta}|\boldsymbol{\alpha}, \boldsymbol{y}) = \ln |\boldsymbol{F}_0| &+ (\boldsymbol{\alpha}_0 - \boldsymbol{a}_0)' \boldsymbol{F}_0^{-1} (\boldsymbol{\alpha}_0 - \boldsymbol{a}_0) \\
&+ n \ln |\boldsymbol{Q}_t| + \sum_{t=1}^{T} (\boldsymbol{\alpha}_t - \boldsymbol{T}_t \boldsymbol{\alpha}_{t-1})' \boldsymbol{Q}_t^{-1} (\boldsymbol{\alpha}_t - \boldsymbol{T}_t \boldsymbol{\alpha}_{t-1}) \\
&+ n \ln |\boldsymbol{H}_t| + \sum_{t=1}^{T} (\boldsymbol{y}_t - \boldsymbol{Z}_t \boldsymbol{\alpha}_t)' \boldsymbol{H}_t^{-1} (\boldsymbol{y}_t - \boldsymbol{Z}_t \boldsymbol{\alpha}_t).
\end{aligned} \tag{A.5.19}$$

Thus, if we had the complete data we could easily obtain the ML-estimates of $\boldsymbol{\theta}$. However, as this is not the case we may find the ML-estimates based on the incomplete data by successively maximizing the conditional expectation of the complete data likelihood. This is done according to the following steps:

1. Find some initial values for the parameters: $\boldsymbol{\theta}^{(0)}$,
2. calculate the incomplete data likelihood $-\ln L(\boldsymbol{\theta}^{(j-1)}|\boldsymbol{y})$; see equation A.5.18,
3. at iteration $j = 1, 2, ...$ use the Kalman Filter and Kalman Smoother to obtain smoothed values for $\boldsymbol{\alpha}_t^{(S)}$, $\boldsymbol{P}_t^{(S)}$ and $\boldsymbol{P}_{t|t-1}^{(S)}$ for $t = 1, ..., T$ based on the parameters $\boldsymbol{\theta}^{(j-1)}$. Use the smoothed values to calculate the conditional expectation of the complete data likelihood

$$\begin{aligned}
Q(\boldsymbol{\theta}|\boldsymbol{\theta}^{(j-1)}) =& E\left\{-2 \ln L(\boldsymbol{\theta}|\boldsymbol{\alpha}, \boldsymbol{y})|\boldsymbol{y}_n, \boldsymbol{\theta}^{(j-1)}\right\} \\
=& \ln |\boldsymbol{F}_0| + \operatorname{tr} \left\{\boldsymbol{F}_0^{-1} \left[\boldsymbol{P}_0^{(S)} + \left(\boldsymbol{\alpha}_0^{(S)} - \boldsymbol{a}_0\right) \left(\boldsymbol{\alpha}_0^{(S)} - \boldsymbol{a}_0\right)'\right]\right\} \\
&+ n \ln |\boldsymbol{Q}_t| + \operatorname{tr} \left\{\boldsymbol{Q}^{-1} \left[S_{11} - S_{10} \boldsymbol{Z}_t' - \boldsymbol{Z}_t S_{10} + \boldsymbol{Z}_t S_{00} \boldsymbol{Z}_t'\right]\right\} \\
&+ n \ln \boldsymbol{H} \\
&+ \operatorname{tr} \left\{\boldsymbol{H}^{-1} \sum_{t=1}^{T} \left[\left(\boldsymbol{y}_t - \boldsymbol{Z}_t \boldsymbol{\alpha}_t^{(S)}\right) \left(\boldsymbol{y}_t - \boldsymbol{Z}_t \boldsymbol{\alpha}_t^{(S)}\right)' + \boldsymbol{Z}_t \boldsymbol{P}_t^{(S)} \boldsymbol{Z}_t'\right]\right\},
\end{aligned} \tag{A.5.20}$$

where

$$S_{11} = \sum_{t=1}^{T} \left(\boldsymbol{\alpha}_t^{(S)} \boldsymbol{\alpha}_t^{(S)\prime} + \boldsymbol{P}_t^{(S)} \right),$$

$$S_{10} = \sum_{t=1}^{T} \left(\boldsymbol{\alpha}_t^{(S)} \boldsymbol{\alpha}_{t|t-1}^{(S)\prime} + \boldsymbol{P}_{t|t-1}^{(S)} \right) \text{ and}$$

$$S_{00} = \sum_{t=1}^{T} \left(\boldsymbol{\alpha}_{t|t-1}^{(S)} \boldsymbol{\alpha}_{t|t-1}^{(S)\prime} + \boldsymbol{P}_{t|t-1}^{(S)} \right).$$

4. Update $\boldsymbol{\theta}_0$ according to

$$\boldsymbol{T}_t^{(j)} = S_{10} S_{00}^{-1},$$
$$\boldsymbol{Q}_t^{(j)} = n^{-1} \left(S_{11} - S_{10} S_{00}^{-1} S_{10}' \right) \text{ and}$$
$$\boldsymbol{H}_t^{(j)} = n^{-1} \sum_{t=1}^{T} \left[\left(\boldsymbol{y}_t - \boldsymbol{Z}_t \boldsymbol{\alpha}_t^{(S)} \right) \left(\boldsymbol{y}_t - \boldsymbol{Z}_t \boldsymbol{\alpha}_t^{(S)} \right)' + \boldsymbol{Z}_t \boldsymbol{P}_t^{(S)} \boldsymbol{Z}_t' \right]$$

to obtain $\boldsymbol{\theta}^{(j)}$.

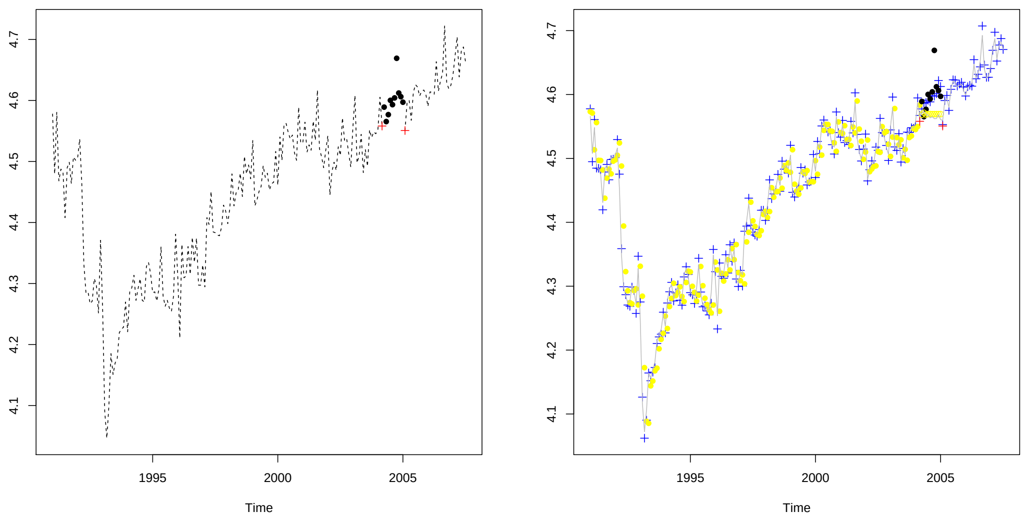
5. Repeat steps 2. to 4. until convergence is achieved.

Note, that in this paper the ML-estimation of the state-space model is achieved via the EM algorithm. We have set $\kappa = 0.001$. Convergence was achieved within 17 iterations.

A.6 Performance of Kalman Filter vs. AR in estimating missing values

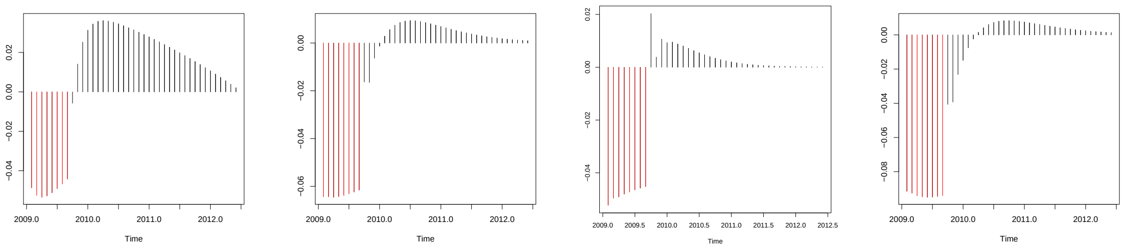
In this section we want to show that constructing a counterfactual scenario based on Kalman Filter values for the missing observations is preferable to approximating these observations by the forecasts of a naive AR-model. We therefore focus on the pre-intervention data, i.e. the time series of domestic vehicle order up to July 2007. Again we treat nine (randomly chosen) observations as missing (April to December 2004). The left panel of Figure A.2 shows domestic vehicle orders (grey dashed line). Observations between the two red crosses, April and December 2004, are treated as missing. They are however shown as black points. We now want to approximate the missing observations by Kalman Filter values (again making use of the information incorporated in the offshore vehicle orders series) and the forecasts of an AR(2)-process fitted to the data. The results are shown in the right panel of Figure A.2. Kalman Filter values are given by the blue crosses (the grey line represents Kalman Smoother values). The yellow dots give the fitted values of the AR(2)-process, while yellow circles show the forecasts of the AR(2)-process. Again, the actually observed values are given by the black dots. As we can see the Kalman Filter values come much closer to the actually observed values than do the predictions based on the AR(2)-process. The root-mean-square deviation of the Kalman Filter values (for the nine missing observations) is 0.0256, whereas for the AR(2)-forecasts it is 0.0414 – approximately 62% higher. Thus, constructing a counterfactual scenario for the German vehicle industry without a scrappage scheme based on the Kalman Filter seems to be the preferable method.

Figure A.2: Performance of Kalman Filter vs. AR-model in estimating missing values.



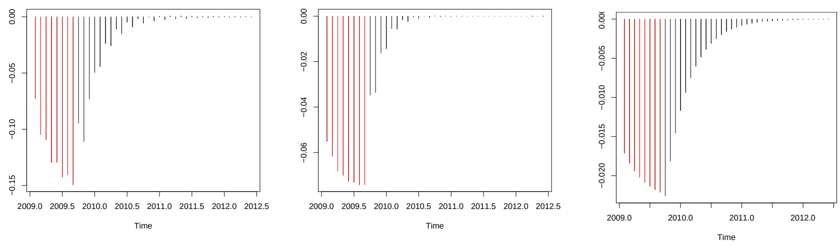
Notes: Left panel – Domestic vehicle orders up to Jul. 2007 with missing observations between Apr. and Dec. 2004; right panel – Kalman Filter values (blue crosses), Kalman Smoother values (grey line), fitted values of the AR(2)-process (yellow dots), forecasts of the AR(2)-process (yellow circles), and actually observed values between Apr. and Dec. 2004 (black dots).

Figure A.3: Distortionary demand effects by sector I



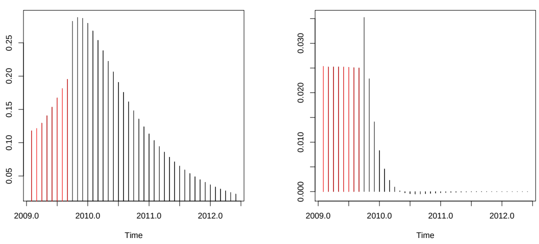
Note: Net transfer functions (from left to right): pharmaceutics, metal, chemicals, electronical/optical devices

Figure A.4: Distortionary demand effects by sector II



Note: Net transfer functions: clothing, electronics, textiles

Figure A.5: Distortionary demand effects by sector III



Note: Net transfer functions: machines, paper