Econometric Game 2017
The Epidemiology of Ugly Shutter Disease

Team 5

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Abstract

This paper studies the adoption of crime prevention devices among Dutch households. Through extensive information on crime, crime prevention behavior and a battery of covariates, we document that Dutch households in the South-East part of the Netherlands utilize intrusive burglary prevention measures to a much higher extent than households in the North-West. This spatial dependence is not merely driven by differences in the criminal environment across the Netherlands. We test and confirm one of the main hypotheses of household crime prevention adoption: that households cope other households in their local network. Furthermore we predict that the whole of the Netherlands will be saturated with window shutters in 15 years given the trend continues.

1 Introduction

Crime rates have been declining in the Netherlands over the last few decades. A large literature is concerned trying to explore the effect of crime preventive behavior on crime rates and vice versa. Alongside the decline crime rates in Netherlands there have been an increased usage of visible crime preventive devices in form of roll-down window shutters. Quite notably, the usage of shutters is concentrated towards the South-Eastern part of the Netherlands bordering Belgium. This could be explained by a higher level or perceived crime level in this region which would cause household to invest more havily in crime prevention. However, we explore whether this concentration of shutters in the municipalities bordering Belgium could be explained by the concept of social contagion. Observing neighbourhs installing shutters can increase the likelihood of installing shutters trough two mechanisms.

There are two mechanisms through which social interaction can affect the roll out of shutters. First, when neighbors install shutters households might be more likely to also install shutters, as they become more 'common' in the area. Shutters are not particularly pretty, but when more households install them, it might be more socially acceptable. Second, when neighbors install shutters household might feel more exposed to burglary, and therefore also invest in shutters. We can not differ these two effects but test the hypothesis of this 'copying effect' explains the geographical patterns in the use of shutters. The install ment of shutters is especially informative when studying the effect of social contagion as they are very visible. Difficulties arise when trying to access the causal effect of such social contagion, as destribed in Manski (1993). The adopting effect of shuters will not be identified when we don't have any informaiton about the prior distribution of shutters. We set-up a model to overcome this issue.

In the first part of the case we visualize the geographical variation of use of shutters and other crime preventive measures based on the crime survey of 2005, 2006, 2007, and 2008. We also visualize the geographical variation in the level of crime and characteristics approximating socioeconomic level within the municipalities. To support the findings of the geographical visualization we formally test whether the spatial distribution conform to Tobler's first law of geography. Also, we test how the probability of a household using shutters vary with longitude and latitude, to investigate whether there is indeed clear geographical patterns in the usage of shutters.

In the second part, we test the hypothesis of 'copying effect' that households copy the preventuve visible behaviour, installment of shutters, of their neighbors. We set-up a spacial lag model to test this hypothesis using the aggregated data at the municipality level. To fully explore the data set we also set-up a LPM model on the household level data, estimating the effect of average shutter the level in the neighborhood on the probability of installing shutters. Overall, we find evidence of the copying effect, that the geographical patterns of shutter usage can be explain by social contagion.

Lastly, we use our findings to predict when the usage of shutters will have spread towards the North-Western part of the Netherlands, by utilizing the predictions form the spatial analysis from above.

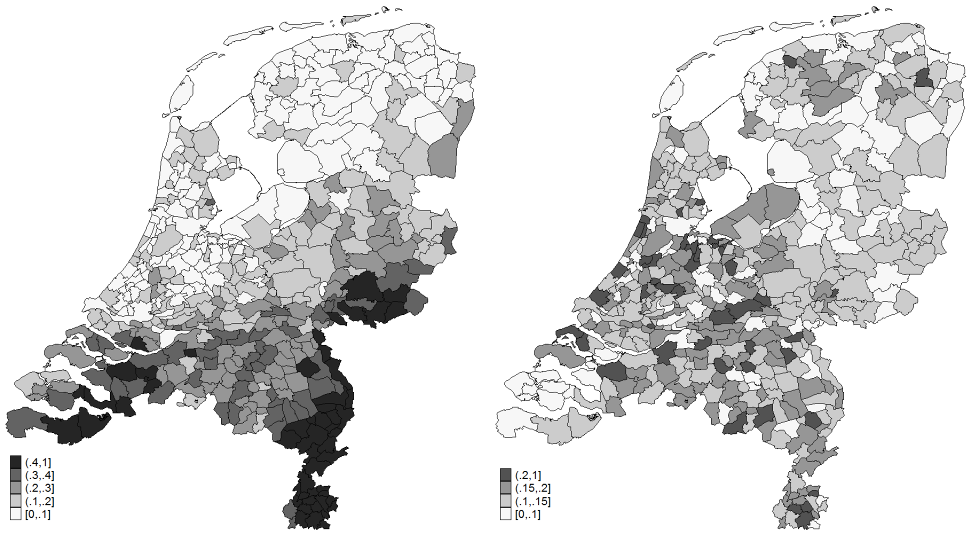
2 Geographical patterns

The use of roll-down shutters as a crime preventive deviced have steadily been increasing since the 1990's. Considering the fraction of household in a municipality with shutters follows a clear geograpical pattern. Shutters are clearly much more prevalant in the South-Eastern part of the Netherlands, bordering Belgium, as depicted in Figure 1a. This pattern is less clear when considering a different crime preventive device - burglary alarms, as depicted in Figure 1b.

One motive for installing shutters is to deter criminals from attempting to commit burglary. An explanation for the prevelance of shutters in the South-Eastern part of Netherlands could be a higher crime rate. However, there is no clear geographical pattern in the burglary rate or assault rate, as depicted in Figure 2a and Figure 2b. Another explanation for the

Figure 1: Geographical variation in burglary prevention

(a) Fraction with shutters (b) Fraction with burglary alarms



geographical pattern could be explained by the fact that shutters are costly. However, the fraction of households investing in shutters is associated with neither the fraction of households with labor income as the most important source of income (Figure 3a) nor the fraction of households within the bottom 20 pct. of the income distribution (Figure 3a). Thus, these choropleth maps do not uncover the explanation for the geographical pattern of shutter adoption observed in Figure 1a. These results motivative our hypothesis that the pattern is driven by the copying effect.

Figure 2: Geographical variation in crime

(a) Burglary rate (b) Assault rate

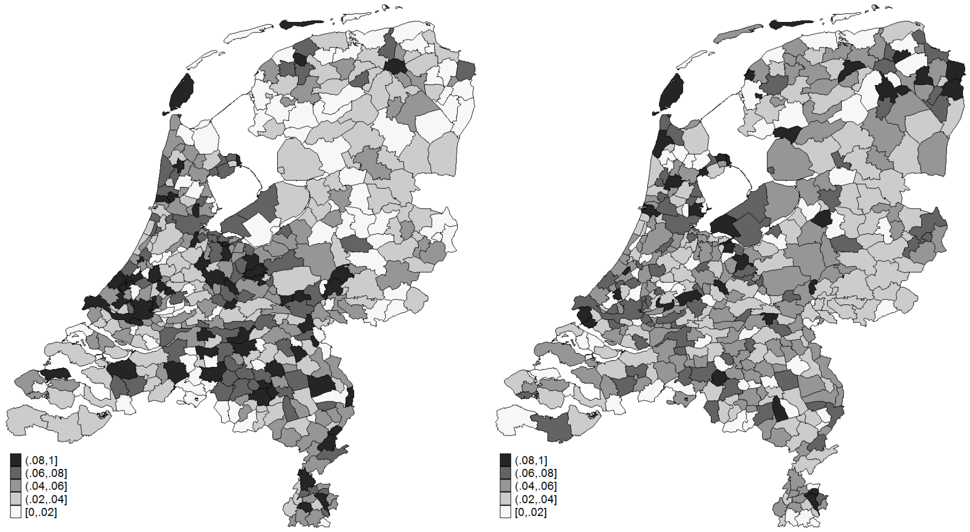
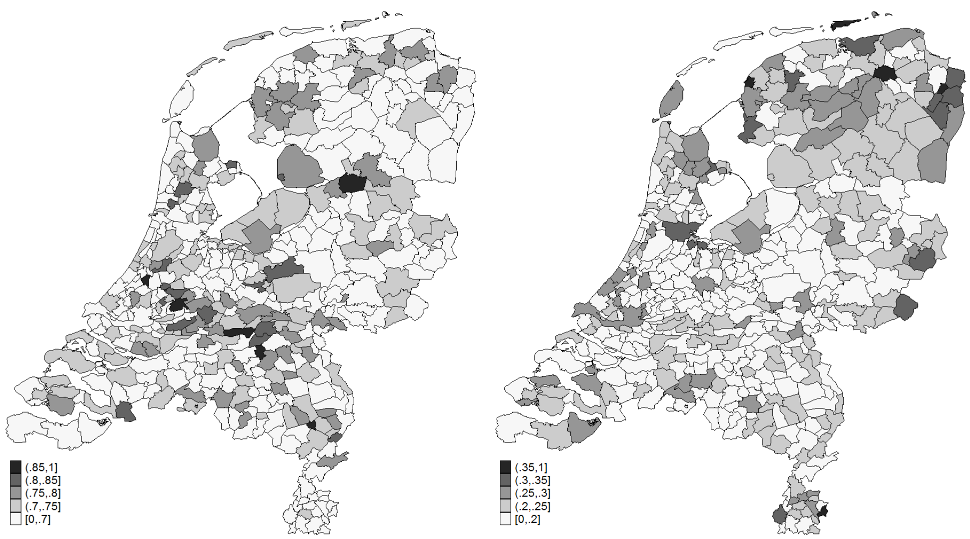


Figure 3: Geographical income variation

(a) Share with main labor market income (b) Share with bottom 20% income



Before exploring this hypothesis further, we document the presence and test the sign of spatial autocorrelation further by means of the Moran's I-statistic. In brief, we compute the degree of similarity between municipality i and j with respect to shutter usage weighted by the degree of proximity between the municipalities, w_{ij}. Note that $w_{ii} = 0$. The statistic is given by the normalized sum of these measures:

$$I = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y})^2 \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}}. \tag{1}$$

Thus, the Moran's I-statistic takes on high values, when municipalities are both similar in their shutter usage and are spatially close. This case is summarized in Tobler's first law of geography stating that "everything is related to everything else, but near things are more related than distant things". We can use 1 to test the Tobler's first law of geography by a simple z-test noting that under the null of no spatial autocorrelation, $E(I) = -1/(N-1)$. As reported in Table 1, we strongly reject the null of no spatial autocorrelation in shutter usage across municipalities. We also show highly significant spatial autocorrelation for other variables measuring burglary prevention and the dummy variable measuring burglary incidences. However, the size of the I-statistic relating to shutter usage is much larger compared to the remaining variables. Hence, there is a stronger tendency for similarities among spatially close municipalities when it comes to shutter usage as compared to bulgary and other bulgary prevention measures.

As a final step in the preliminary analysis, we estimate the correlation between longitudinal and latitudinal coordinates and the probability of having shutters. Table 2 shows the results: shutter usage increases in longitude and decreases in latitude. Hence, non-surprisingly, the probability of using shutters is lowest in the Northwest. These results are robust towards controlling for municipality, household and individual characteristics.[1] We also show in appendix that a probit model gives similar results.

[1] Controls include population and burglary rate on municipality-level, household income bins, and individual-level higher-level education, origin, gender, age, and age squared.

	I	E(I)	sd(I)	z	p-value
Shutter usage	0.272	-0.002	0.004	74.953	0.000
Burglary alarm	0.054	-0.002	0.004	15.507	0.000
Car alarm	0.041	-0.002	0.004	11.850	0.000
Doorlocks	0.069	-0.002	0.004	19.528	0.000
Burglary	0.035	-0.002	0.004	10.119	0.000

Table 1: Moran's I-test for Tobler's First Law of Geography

	No controls	Controls
Longitude of municipality	0.067***	0.060***
	(0.007)	(0.006)
Latitude of municipality	-0.209***	-0.211***
	(0.009)	(0.009)
Observations	65033.000	64819.000

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Estimating the variation of shutter usage across longitudinal and latitudinal coordinates. Standard errors clustered on municipality-level.

3 Testing the Copying Effect Hypothesis

In this section, we test the copying effect hypothesis stating that . Note that we are not aiming at discriminating between potential mechanisms for the copying effect hypothesis; this would surely be an interesting question, however, currently available model frameworks are not designed for explaining such mechanisms Liesenfeld, Richard, and Vogler (2017). It is instructive to begin this exercise by discussing the ideal experiment that would allow us to uncover the explanation of the geographical pattern in shutter usage. This ideal experiment motivates our approach towards testing the hypothesis.

3.1 The Ideal Experiment and Limitations of the Analysis

In the ideal experiment, we would - at time 0 - randomly allocate shutters to households, thereby causing random variation in the neighborhood shutter uage rate from the viewpoint of each household. In order to evaluate the effect of social contagion, we would measure the shutter adoption rate in these households after an appropriate period of time in which believe that the copying effect has had time to establish (time 1). Because of the random allocation, we could test the copying effect hypothesis by estimating the causal spatial dependence in shutter roll-out. Formally, we could run a simple spatial-lag regression of the shutter adoption rate in household i on the spatial lag wrt. household j, $w_{ij}y_j$, for $j = 1, ..., n$:

$$y_i = \rho \sum_{j=1}^{n} w_{ij} y_j + \varepsilon_i, \ \varepsilon_i \sim N\left(0, \sigma^2\right),$$

where ρ is the spatial dependence parameter. Lee (2004) shows that this model is consistently estimated by (quasi) maximum likelihood; note, however, that the OLS estimator is inconsistent. Estimating ρ at time 0 would cause $\rho = 0$ by construction due to randomization. In contrast, at time 1, $\rho = 0$ only if there is no copying effect in shutter adoption. If $\rho > 0$, there is an effect running from neighbors to households, suggesting a copying effect. As a consequence of the randomization, there are no confounders ruining the test of $\rho = 0$ as a test of the copying effect hypothesis. Thus, inclusion of additional controls is not necessary (but it can decrease standard errors on the estimator of ρ). If we furthermore could observe the shutter adoption rate in the neighborhoods at fixed points in time between time 0 and 1, we could analyse the rate of shutter adoption.

Several limitations in data availability prevents us from conducting the analysis above:

1. Firstly, and most importantly, the randomized experiment is obviously not observable in the real world. As a serious consequence, there are unobserved confounders hidden in ε_i. For instance, if burglary rates are geographically clustered and positively correlated with shutter roll-out, the estimate of ρ will be biased upwards, which is a problem for our test of the copying effect hypothesis ($\rho = 0$). To reduce or eliminate this source of bias, we rely on conditional independence as detailed in Section 3.2.1.

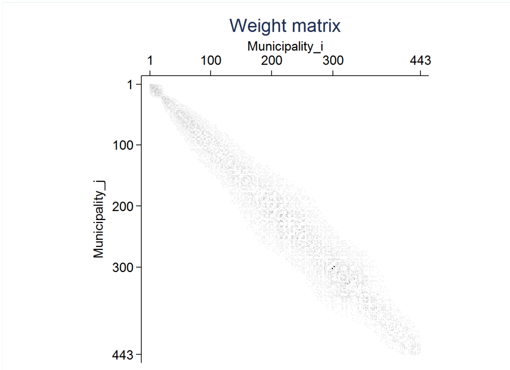
2. Secondly, the construction of weight matrix, w_{ij} for $i, j = 1, ..., n$, has econometric impact. In particular, it is well-known that the spatial correlation coefficient is high when using an unrestricted weight matrix Gibbons and Overman (2010). Therefore, it is common practice to restrict the spatial weights. However, the choice of restricting (or not restricting) the spatial weigths should be motivated by theoretical considerations and not driven by data. This issue is discussed futher below.

3. Finally, the geographical identifier in the supplied data is given by the municipality, not on household levels. A straightforward circumvention of this problem is to estimate a spatial lag model on the adoption rates across municipalities rather than households. This reduces the sample size substantially, which decreases the power of the test. To avoid this problem, we merge the waves of each of the data sets. We do not expect that this will disturb the analysis due to the permanent nature of shutter adoption: once a household has installed shutters, it will continue to have shutters. Furthermore, we supplement the municipality-level analysis with an analysis on the household-level. This is the discussed further in Section **??**.

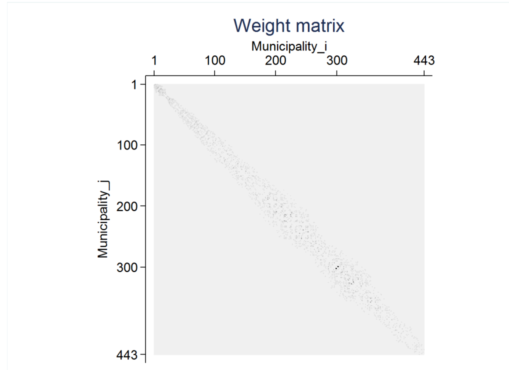
3.2 Municipal-Level Analysis relying on Conditional Independence

3.2.1 Spatial Regression

As discussed above, presence of unobserved confounders is a main issue when testing the copying effects hypothesis. Therefore, we include additional observed variables believed to be correlated with both y_{-i} and y_i, i.e., burglary rates, income, education, crime rates, and littering rates. Formally, we estimate



(a) Weight matrix sorted by distance to Vaals.



(b) Weight matrix sorted by distance to Vaals.

Figure 4: Weight matrix specifications.

$$y_i = X_i\beta + \rho\sum_{j=1}^{n} w_{ij}y_j + \varepsilon_i$$

where X_i is the vector of included controls. Assuming that X_i is constructed such that $\mathbb{E}(\varepsilon_i|X_i) = 0$, we can test the copying hypothesis test from a test of $\rho = 0$ similar to the ideal experiment case.

We noted in the discussion above that it might be appropriate to restrict the spatial weights. In particular, it is not sensible to expect the copying effect to be present across all of the Netherlands: households in the very South are not likely to affect households in the very North even if shutter adoption is socially contangious. Therefore, we restrict the weighting matrix such that the spatial lag enters locally only as illustrated in Figure 4a. Figure 4b shows the unrestricted weight matrix as reference. Specifically, we set all weights to zero that are below a treshold given by the minimal radius from the centroid of all municipalities that ensures they have at least one neighbouring municipality.

The estimation results are shown in Tabel **??**, where we note that

1. The spatial autocorrelation coeficient is estimated to be positive and highly signficiantly different from zero for shutters usage. This result conform with the copying effects hypothesis.

2. The spatial autocorrelation with respect to adoption of burglary alarms is also significant, but much lower than that of shutter adoption. Thus, there is stronger spatial correlation between burgalary prevention methods that are observable (shutters) compared to unobserable ones (burglary alarms).

	Shutters	Burglary alarms
Percent burglaries	-0.319**	0.109
	(0.118)	(0.084)
Municipality population	-0.000	-0.000
	(0.000)	(0.000)
Average household income	0.002	0.037***
	(0.014)	(0.010)
Percent daily policing	-0.095	-0.032
	(0.056)	(0.039)
Average vandalizing	0.024	-0.005
	(0.016)	(0.011)
Average street littering	-0.001	0.015
	(0.025)	(0.018)
ρ	0.932	0.019
	(0.019)	(0.080)
Observations	443	443

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Spatial lag model with controls

3.2.2 Temporal Spatial Regression

The copying effects hypothesis is highly related to changes through time. In the ideal experiment, we would measure the rate of shutter adoption at time 0 and 1. The available data allows us to make a similar comparison by using the waves from the ERV data set (1993-1995). The geographical variation in this data is analyzed in Figure 5, which show the following main points:

1. The geographical pattern of shutter adoption observed in the recent data is also present in the data from the 1990s (Figure 5a), but to a much lesser extent. This observation conforms with the copying effects hypothesis: shutter usage is spreading in a Northweastern direction through time as more and more households are influenced.

2. As in the recent data set, the geographical pattern in shutters adoption is not shown with burglary alarms (Figure 5b).

3. Finally, the fraction of burglary does not exhibit the pattern observed in shutters adoption during the years 2005-2008 (Figure 1a). This is an important observation. We can reasonably expect that increased shutter usage results in fewer burglaries. If the pattern in Figure 1a was identifiable from the choropleth of burglary rates in the 1990s, the pattern would be explained by high burglary in the past rather than the copying effect hypothesis. Fortunately, Figure 5c indicates that this is not the case. During the first wave of crime surveys there is no clear geograpical pattern in the usage of crime preventive devices (visible, shutters, and non-visible, burglary alarms), as depicted in Figure 5b and Figure 5c.

We proceed by exploring the temporal effects formally by estimating a temporal spatial lag model:

$$y_{1i} = X\beta + \kappa y_{0i} + \rho \sum_{j=1}^{n} w_{ij} y_{1j} + \varepsilon_i,$$

where y_{1i} and y_{0i} denote the shutter adoption rate in the waves 2005-2008 (time 1) and 1993-195 (time 0), respectively. The results are reported in Table **??**

The estimation results are shown in Tabel **??**, where we note that

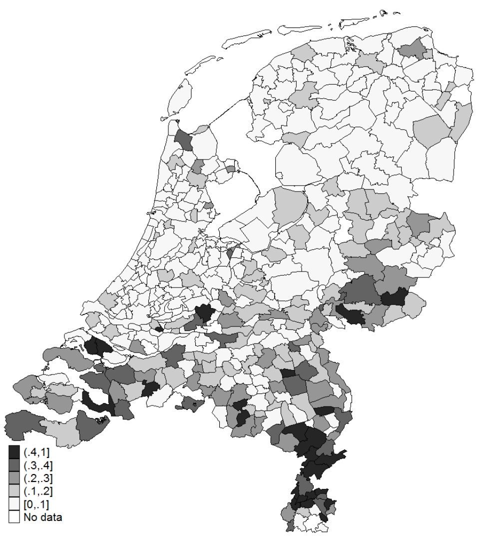
1. The spatial autocorrelation coeficients are similar to Table **??**.

2. The autoregression coefficient of shutters is postive and highly significant. The autoregressive coefficient of burglary alarms is near zero and insignificant. This shows that the growth in shutter installment increases in the average roll out within the municipality.

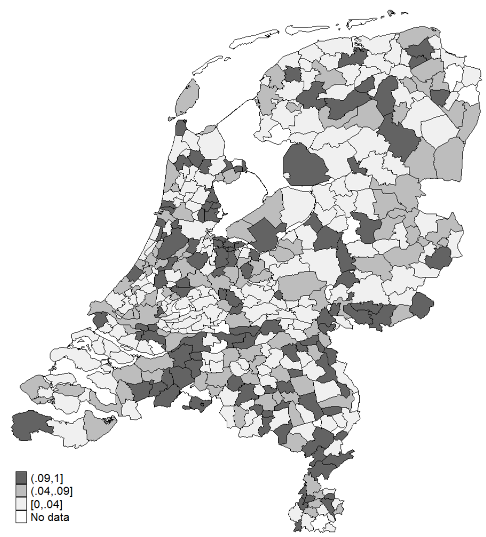
We will now contiunue the analysis on individual data.

Figure 5: Geographical variation in 1990s

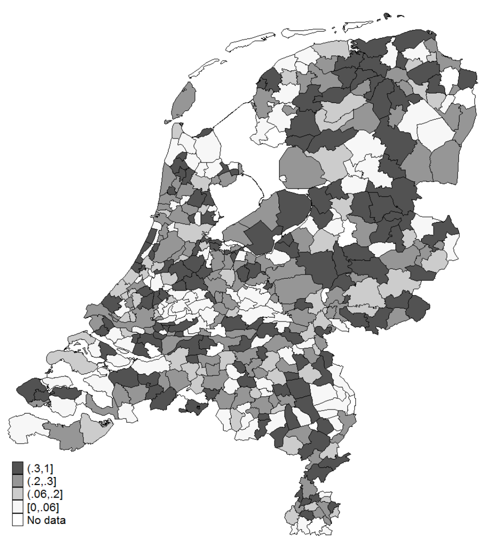
(a) Fraction with shutters



(b) Fraction with burglary alarms



(c) Fraction with burglary



	Shutters	Burglary alarms
Percent shutters before	0.130***	
	(0.023)	
Percent burglaries	-0.398***	0.113
	(0.120)	(0.087)
Municipality population	-0.000	-0.000
	(0.000)	(0.000)
Average household income	0.012	0.047***
	(0.015)	(0.011)
Percent daily policing	-0.070	-0.035
	(0.076)	(0.054)
Average vandalizing	0.013	-0.008
	(0.016)	(0.011)
Average street littering	-0.009	0.017
	(0.026)	(0.018)
Percent burglary alarms before		0.004
		(0.023)
ρ	0.877	0.397
	(0.025)	(0.082)
Observations	423	423

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Spatial lag model with time dependence and controls.

3.3 Household level evidence

With ideal data, we would know the exact geographical location of all households in our dataset. With this information, we would be able to estimate the spatial effects of shutters on 'copying behaviour' on a very detailed level. In the preceding section, we utilized the spatial information available on the municipality level. We generally expect copying effect to work through relatively short distances, which are not perfectly captured by between-municipality distances.

In this subsection, we therefore seek to utilize the individual level distances. Instead of estimating effects of the euclidean distance (only measured on the municipality level in our dataset) in a spatial econometric model, we a different measure capturing network effects: within municipality shutter adoption. The main idea is to estimate how shutter adoption by all other households in your specific municipality affects your probability to have shutters. We look at the dependence between shutter 0/1 for household i and the shutter rate for all other household than i in the same municipality. To do so we

- Label these other household as neighbors in some sense.
- Don't include household i in the calculation of mean shutter rate in the same municipality, because this mechanically induced correlation between mean adoption rate and adoption for household i.
- This neighborhood/municipality mean adoption rate measure can be labeled a leave-one-out measure.

3.4 Ideal experiment

Let's again consider the ideal experiment and the test of the copying hypothesis.

- We randomly allocate shutters to households and run the simple OLS regression for household i in municipality m

  $$y_{im} = \beta_0 + \gamma_1 \mathrm{S}_{-i,m} + \varepsilon_i$$

  where $\mathrm{S}_{-i,m}$ is the average shutter rate for all households in municipality m except for household i.

- Due to the random allocation of shutters, the $\hat{\gamma_1}$ will be the estimate of the peer-effects on shutter adoption and a test of $\hat{\gamma_1} = 0$ is a test of the copying effect hypothesis. In other words, $\hat{\gamma_1}$ is an estimate of the effects of other households within the municipality on the individual decision to adopt shutters.

- The idea behind this leave-one-out measure is to overcome the reflection problem of Manski (1993), when the researcher observed the distribution of behaviour in a population without any information on the prior distribution.

3.5 Assuming conditional independence

Unfortunately, economist are rarely able to conduct randomized control trails. However, relying on a set of assumptions we will be able to infer whether the coyping effect is present. To

- Since we can't run the ideal experiment we have to rely on the conditional independence assumption or find some source of exogenous variation.
- As a first step, we try to control for relevant factors which might lead to bias if left out of the eqution. Formally, we can run linear regressions on

$$y_{im} = X\beta + \gamma_1 \mathrm{S}_{-i,m} + \varepsilon_i$$

  where X is a vector containing a large set of additional controls.

- If we assume that we can control for confounding factors to an extent where $\mathbb{E}(\varepsilon_i \gamma_1 | X) = 0$, we can test the copying effect hypothesis by a test of $\hat{\gamma}_1 = 0$ (much like in the ideal experiment)
- This is a very strong assumption. Issues with unobserved covariates!
- Regression results imply that there is indeed a strong effect of the municipality level fraction of shutters on the probability of having shutters at the household levels. When controlling for other households characteristics and municipality characteristics the effect decreases, but not much.
- Loosing observations because of missing controls.
- However, in this naive regression endogenity issues arrise as

Table 5: Household level LPM

	(1) Shutters	(2) Shutters
S(i,m)	0.926^{***}	0.947^{***}
	(55.93)	(89.35)
Controls	Yes	No
Observations	25880	65033

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.6 A 2SLS approach

To overcome the endogeneity issues in the preceeding sections, we try an instrumental variables approach. We want to run a 2SLS model as shown below

$$\begin{aligned} y_{im} &= X\beta + \gamma_1 \mathrm{S}_{-i,m} + \varepsilon_i \\ \mathrm{S}_{-i,m} &= \Lambda\beta + \delta Z + \nu_i \end{aligned}$$

where the bottom equation is the first stage.

Without an instrument, the problem is the potential correlation between shutter$_{-i,m}$ and ε_i due to unobserved factors such as other types of crime or local institutional rules (such as a potential rule requiring some household to install shutters)

We are looking for an instrument Z which affect $\mathrm{S}_{-i,m}$ but isn't correlated with ε_i. if we can find it, we can again test the copying effect hypothesis as a test of $\hat{\gamma}_1 = 0$

- Instrument 1: the average shutter rate in municipality m in the 1990'ies.
  - This instrument is highly predictive of the shutter rate in the late 00's
  - It is uncorrelated with contemporaneus shocks to shutter adoption.

Instrumenting the shutter fraction at the municipality level with the shutter fraction in the mid 1990s the effect is similar to the results above.

Table 6: Household level LPM, 2SLS

	(1) Shutters	(2) Shutters
S(i,m)	0.986***	1.000***
	(39.97)	(63.29)
Controls	Yes	No
Observations	25587	64303

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.7 Effects on less salient crime prevention devices

We provide further evidence on the copying effect hypothesis by estimating models similar to the main models on shutters, but estimated on crime preventive variables that are not visible from the outside. If the findings in Table **??** were driven by the fact that households investing in shutters are generally more risk adverse or concerned with the risk of crime we would expect to find similar results when considering other crime preventive devices.

The spatial effect on these variables should be smaller in magnitude than the effect on shutters, because these devices are not visible from the outside and network effects should be less pronounced.

Regression results indicate that the copying effect is much less when considering less salient crime preventive devices, as burglary alarms and car alarms. Thus, the findings in Table **??** seems to be driven by the fact that sutters are very visible in the street picture.

Table 7: Household level LPM, robust

	(1) Burglary alarm	(2) Burglary alarm	(3) Car alarm	(4) Car alarm
S(i,m)	0.0418**	0.0509***	0.121***	0.142***
	(2.76)	(5.24)	(5.50)	(10.13)
Controls	Yes	No	Yes	No
Observations	25880	65033	25880	65033

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4 Predicting full out-roll of shutters

4.1 The simplest prediction

Even if the copying effect exists we would never observe all household installing shutters, simply for practical reasons. Living on the 10'th floor of a building the risk of burglary through the window is diminishing small. Also, some old buildings might be legally prevented from installing shutters. Thus, full out-roll of shutters does not imply 100 pct. coverage. The 95'th percentile of shutter coverage within municipalities in the second wage of crime surveys is 51 percentage. **Thus, we define full roll-out as 51 percent of all households using roll down window shutters.**

The simplest prediction of the time before full roll-out of shutters is given by finding the percentage increase over the years between first and second wave of the crime survey. The average shutter fraction in increased with 8 pct. over the 12 years (1994-2006) between the first and second wave of the crime survey. Ignoring spatial effects and extrapolating this percentage increase over every period (consisting of 12 years) imply, that the Netherlands would be fully covered (more than 51 percent of households) by shutters in 2020, as depicted in 6

4.2 A sequential prediction system

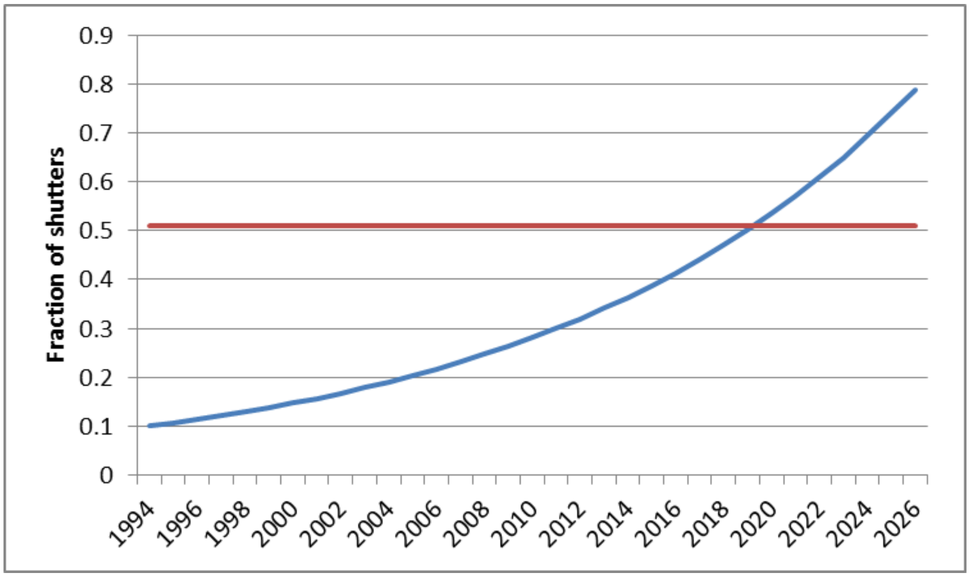
The simple predictions presented above are easy to derive and interpret. However, because they fail to take the spatial dependence into account they are not likely to give a precise picture of the evolution in the rate of households with shutters. In the preceeding sections, we estimated a model allowing for both spatial and temporal dependence in the adoption of shutters. We apply this model in a sequential prediction analysis.

We assume that the covariates are stable ahead in time such that we can disregard these in the prediction model, which becomes

Table 8: The simplest model of prediction

	Fraction
First wave	0.10
Second wave	0.18
	Percentage increase in fraction of shutters
Between first and second wave	8
Per year	0.6

Figure 6: Roll out given simplest prediction



$$y_{1i} = \beta_0 + \kappa y_{0i} + \rho \sum_{j=1}^{n} w_{ij} y_{1j} + \varepsilon_i$$

with estimated paramters equal to $\hat{\beta}_0 = 0.011$ $\hat{\kappa} = 0.13$ $\hat{\rho} = 0.83$. With these parameters, we propose a sequential prediction system. The prediction system utilizes the estimated parameters from the model and adds a structural assumption by restricting the model such that households cannot de-install shutters. In other words, we impose structure by $\hat{\kappa} = 1$. This assumption essentially assumes that households will never choose to de-install an already installed shutter (and hence never de-install a shutter in response to a lot of neighbors without shutters). The workings of the system is described in two steps:

1. **Time prediction step**: Using only the estimate of β_0 along with $\kappa = 1$, we do a 1-step ahead prediction in time for all observations on the right hand side of the equation above. This gives us a prediction for each municipality which does not take the spatial dependence into account. This corresponds somewhat to assuming that time acts as a deterministic process which drives shutter adoption (independent of spatial dependence). To sum up, we predict

$$y_t^{(1)} = \hat{\beta}_0 + \hat{\kappa} y_{t-1}^{(2)},$$

where $y_{t-1}^{(2)}$ is obtained in step 2 and initialized by the observed shutter adoption rates from 2005-2008.

2. **Spatial prediction step**: Using the predictions from step 1 and the estimated parameters, we predict the shutter rate for each observation. In this way, we take the spatial dependence into account. To sum up, we predict

$$y_t^{(2)} = y_t^{(1)} + \hat{\rho} \sum_{j=1}^{n} w_{ij} y_{tj}^{(1)}$$

To see how the mechanics work for one-step ahead prediction, consider an extreme example with two municipalities A and B and a weight of 1 on each neighbor. Initially, A has 0% shutters and B has 50%. Let $\hat{\beta}_0 = 0.1$, $\hat{\kappa} = 1$ and $\hat{\rho} = 0.5$. $\hat{\beta}_0 = 0.1$ means that shutter adoption is expected to increase by 0.1 in each time period. In step 1, we get the following step 1 predictions,

$$\begin{aligned} y_{tA}^{(1)} &= 0.1 + 1 \cdot 0 = 0.1 \\ y_{tB}^{(1)} &= 0.1 + 1 \cdot 0.5 = 0.6 \end{aligned}$$

In the second step, we'll then get

$$\begin{aligned} y_{tA}^{(2)} &= y_{tA}^{(1)} + 0.5 \cdot y_{tB}^{(1)} = 0.4 \\ y_{tB}^{(2)} &= y_{tB}^{(1)} + 0.5 \cdot y_{tA}^{(1)} = 0.65 \end{aligned}$$

Thus, the shutter adoption rates increases by 0.1 for for municipalities without accounting for spatial dependence. When accounting for spatial dependence in step 2, the difference between the municipalities decreases as more households in munipality A installs shutters as their neighbouring municipality B has a high shutter adoption rate.

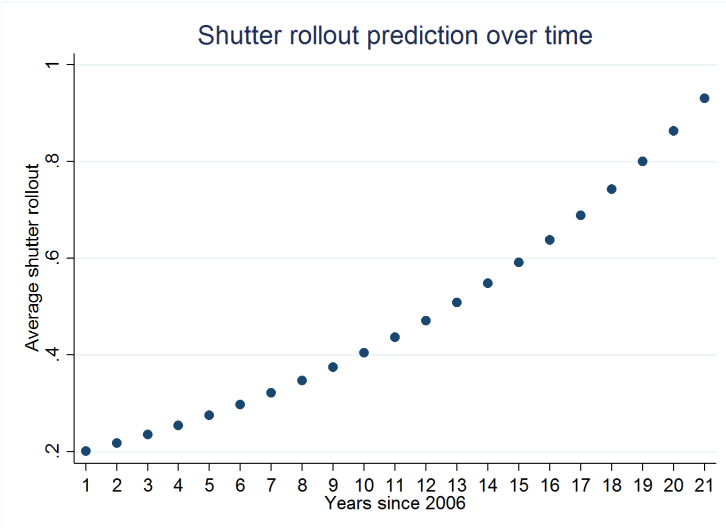
4.2.1 Prediction results

The figure below shows the

5 Conclusion

In this case we have investigated the epidemiology of the ugly shutter disease. In the second wave of a nation wide crime survey a clear geographical pattern of roll-down shutters prevailed, emerging from the Belgium border. Puzzling, this trend of increased shutter usage does not seem to correlate with other types of non-visible crime preventive behavior. We test whether this pattern could be explained by the theory of social contagion, whether an increased usage of this visible crime preventive devices is caused by households wishing to 'look like' their neighbors. The explanation for this 'copying effect' could be related to households being

Figure 7: Years ahead prediction, aggregate



more likely to also install shutters, as they become more 'common' in the area. Shutters are not particularly pretty, but when more households install them, it might be more socially acceptable. Second, when neighbors install shutters household might feel more exposed to burglary, and therefore also invest in shutters.

We set-up a spatial lag model to test this hypothesis and find that we can not reject that the trend is driven by this copying effect. We use the results from our model to predict when the use of shutters will have 'spread' to the rest of the Netherlands, for all the households for which it makes sense to install shutters. We find that the use of shutters will have spread throughout the Netherlands 15 years after the second wave of the crime survey taking spatial correlation into account.

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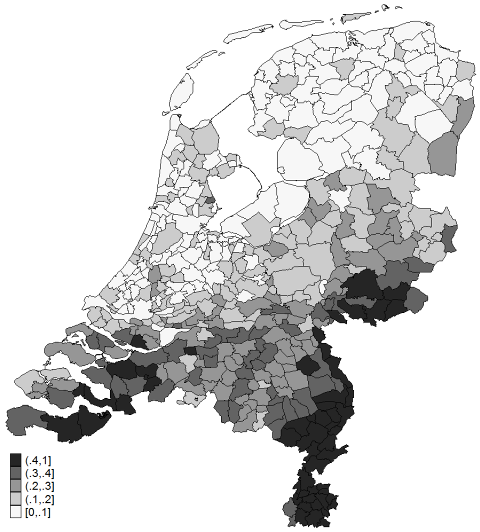
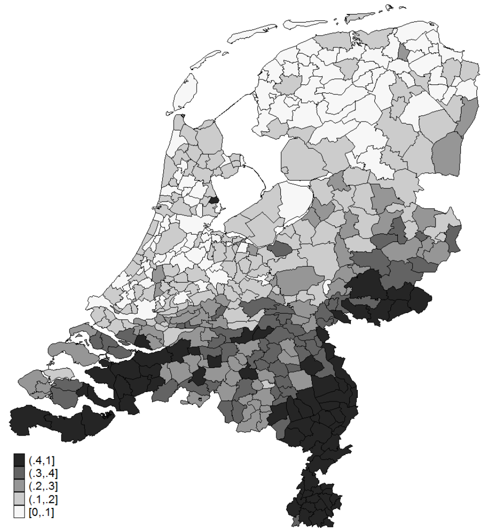
Figure 8: Prediction of Shutter Adoption Rates

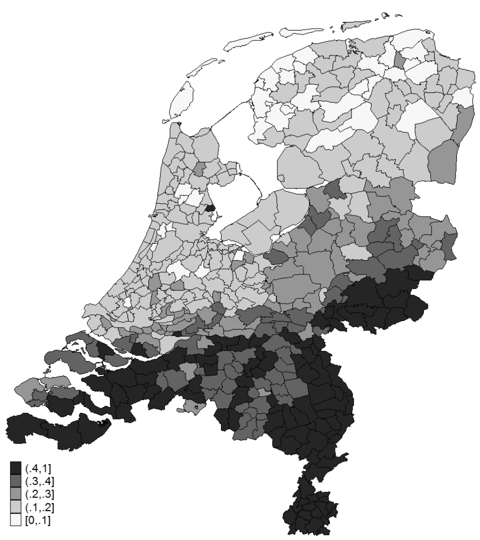
(a) Current (waves 2006-2008)



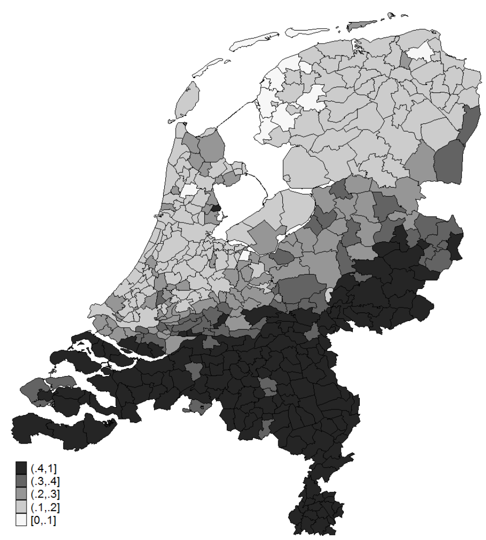
(b) 3-years ahead (2009)



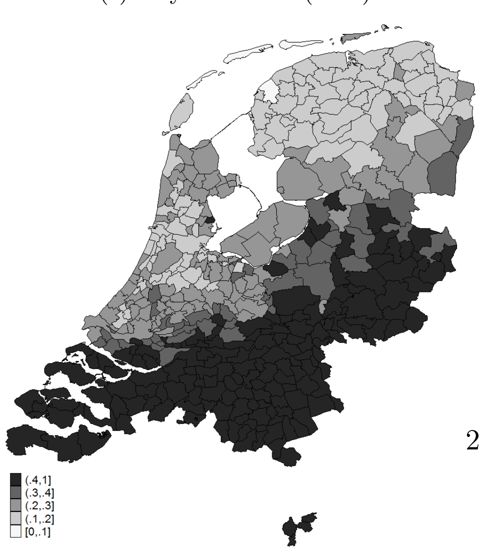
(c) 6-years ahead (2012)



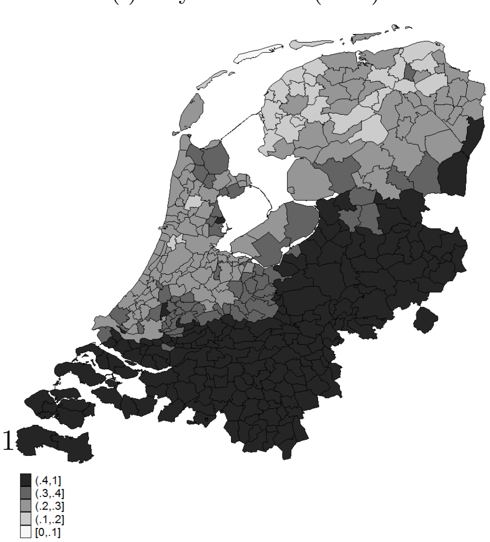
(d) 9-years ahead (2015)



(e) 12-years ahead (2018)



(f) 15-years ahead (2021)



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