Econometric Game 2017
Chasing Causality: The Effect of Shutter Usage on Burglary Victimisation

Team 7

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Abstract

This paper studies the causal effect of using roll-down window shutters on burglary victimisation. We identify a discontinuity in the shutter usage across the large river of Maas, which we use to uncover causal effects in a quasi-experimental fuzzy regression discontinuity design. We find a small positive significant result when estimating the effect on individual-level data, which we interpret in a non-causal way due to non-robustness towards bandwidth selection. We provide tentative evidence that this result reflects existence of heterogeneity in the effect.

1 Introduction

Crime rates have been declining in the Netherlands over the last few decades. A large literature is concerned with exploring the effect of crime preventive behaviour on crime rates and vice versa. In this paper, we look at a particular form of crime and crime preventive device; specifically, we aim at identifying the causal effect of using roll-down window shutters on burglary victimisation as measured by both burglary incidences and attempts.

While the correlation between shutter usage and burglary victimisation is easy to document, it is much more complicated to identify the causal relationship. In particular, we need to account for the possibility that households install shutters as a reaction to burglary victimisation rather than the other way around. Also, the correlation may be driven by unobserved confounders. In result, a simple regression of the shutter adoption rate on burglary and burglary attempts is not ensured to uncover the causal relationship that we are interested in analysing. This case is a clear illustration of why we need **econometricians** to answer these types of questions to identify the causal relationship by utilizing exogenous variation. Data scientists could easily end up mistaking correlation for causality.

We circumvent these issues by exploiting geographical patterns in the shutter adoption rate as exogenous variation. We identify that shutter usage is concentrated towards the South-Eastern part of the Netherlands bordering Belgium. In particular, we identify a discontinuity in the shutter usage across the large river of Maas. We use this observation in a regression discontinuity design to uncover the causal effect. We augment the crime survey data by using google maps to measure the distance to Maas for each municipality. We do so by placing 20 markers in the rivers of Maas and recording the coordinates of each marker. We set-up a fuzzy RD design to uncover the causal effect of shutters, by instrumenting the shutter variable with the distance to Maas. We do not find evidence of any causal relationship between the use of shutters on burglary victimisation.

Another important consideration when considering the effect of shutters on crime is the so-called *displacement effect*: while it is highly likely that window shutters prevent burglary for the particular households with the shutters installed, burglaries may not decrease overall in the neighbourhood as burglars can simply attack households within the neighbourhood that have not adopted shutters. Thus, we keep in mind that in a municipality-level analysis, the measured effect of window shutters is a total of the direct burglary-prevention effect and the displacement effect.

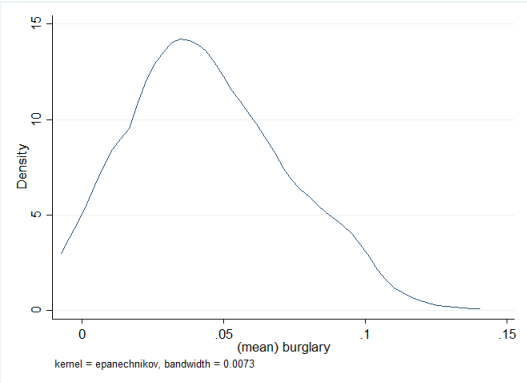
The paper is organised as follows. We begin by describing the data and exploring geographical patterns. Then, we explore a naive approach that identify the relationship between the shutter adoption rate and burglary victimisation measures. Acknowledging that this method **does not** identify causalities, we describe the ideal experiment and the limitations we face that complicates our analysis. The main analysis of the paper attempts to uncover the causal effect of shutter usage and burglary victimisation. We then investigate whether this finding could be explained by the existence of heterogeneous treatment effects from shutter usage. Thus, we explore whether there is any heterogeneity in the effect of shutters on burglary victimisation. It could be, that the effect of shutters on burglary victimisation differ depending on whether a household is surrounded by households using shutters.

2 Data Description

The data stems primarily from a crime survey conducted in the Netherlands yearly from 2005 to 2008 (VMR). We also use earlier data provided by Statistics Netherlands based on a survey conducted in 1993, 1994, and 1995 (ERV). We are mainly interested in variables measuring shutter usage and burglary victimisation across the Netherlands. Fortunately, very few households experience burglary. In order to increase power in our analysis, we pool burglary and burglary attempts as measurements of burglary victimisation. In 35 municipalities no respondents had experienced burglary in the second wave of the crime survey. Figures **??** , 1b , and 2 plot the kernel densities of burglary victimised households and shutter usage.

Figure 1: Kernel densities of burglary victims

(a) Fraction of burglaries



(b) Fraction of burglaries including burglary attempt

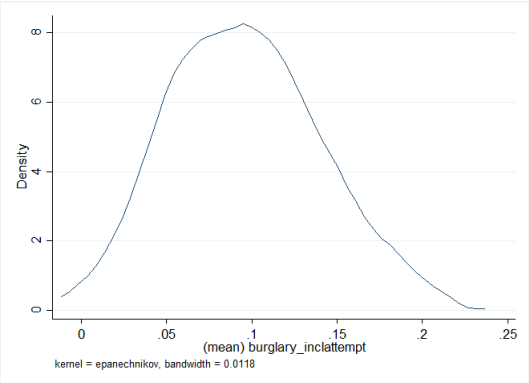


Figure 2: Kernel density of shutter usage

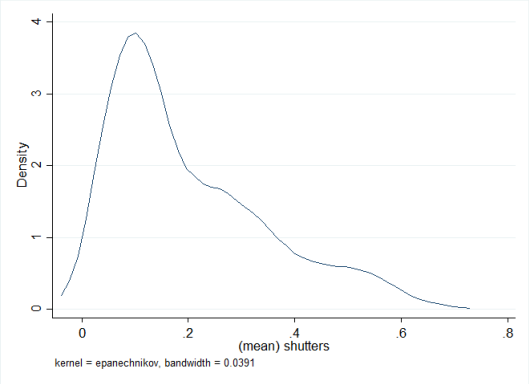
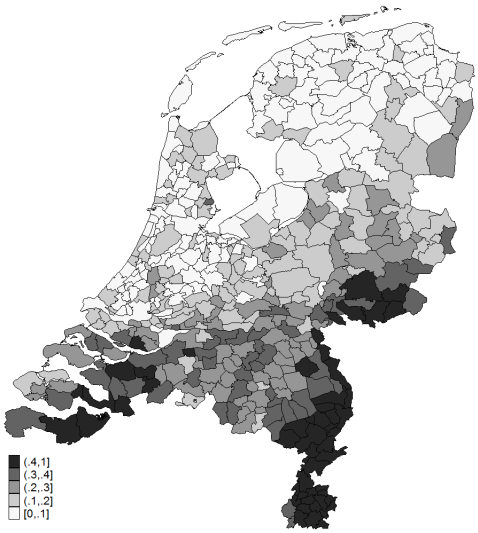
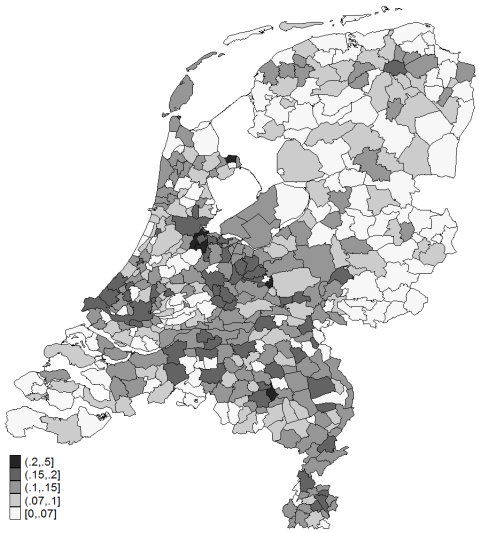


Figure 3: Geographical variation in burglary and prevention

(a) Fraction with shutters



(b) Fraction with burglary alarms



The use of roll-down shutters as a crime preventive device have steadily been increasing since the 1990s. Considering the fraction of household in a municipality with shutters follows a clear geographical pattern. In particular, shutters are clearly much more prevalant in the South-Eastern part of the Netherlands, bordering Belgium, as depicted in Figure 3a. The geographical pattern in fraction of households having experienced a burglary or attempt is depicted in Figure 3b. It seems that the two follow the same geographical pattern. In Figure 4a and 4b the fraction of households having experienced burglary and assault is depicted.

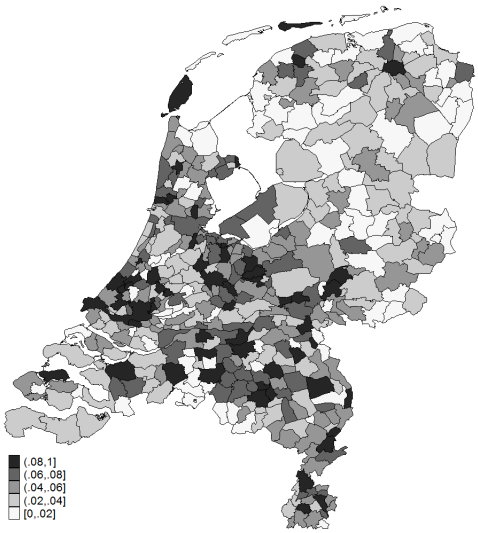
3 The Ideal Experiment and Data Limitations

Let us consider the ideal experiment for identifying the *causal* direct effect of installing shutters in a household on burglary victimisation. Conceptually, we distinguish between ***overall effects*** at the municipality level and ***direct effects*** at the household level. Aggregating direct effects by municipalities does not nessesary sum to overall effects. Any differences are considered ***displacement effects***, namely that putting shutters on your windows might increase the risk of burglary for your unprotected neighboors. To indentify causal direct effect, we need an experiment that randomly allocates shutters to households such that we avoid the possibility of reverse causality; that burglary victimisation is likely to affect the adoption rate of shutters. Randomization also overcomes the issue of unobserved confounders.

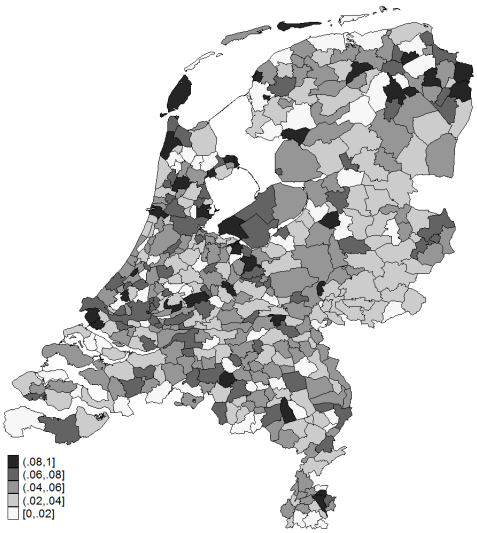
- **1:** Randomly assign households to install window shutters. Perfect randomization secures no differences in baseline burglary risk and other characteristisks.

Figure 4: Geographical variation in crime

(a) Burglary rate



(b) Assault rate



- **2:** Mesasure the difference in burglary victimisation between the treatment and control group.

Given that perfect randomization is possible controls for baseline characterstics would need to be included. For the use of repeated cross-sections it would also be needed to assume no systematic geographic change in the Netherlands burglary victimisation correlating with the assignment. One example of such systematic changes is introducing large-scale police reforms. We conjecture that such events are known and thus in case the assumption of no systematic change fails, we are able to control for these.

To be able to distinguish between direct and overall effects, one should considder differences between effects measured at household level versus effects meassured at the municipality level.

Several limitations in data availability prevents us from identifying the causal effect as easily as described above:

1. Firstly, and most importantly, the data made available has not been collected in accordance with the randomised experiment described above. Instead, the data provides the shutter adoption rate at two time periods, but where the decision of installing shutters have been made non-randomly by the individual households. Thus, we need to identify an alternative source of exogenous variation, which we find in the geographical variation documented in the previous section.

2. Secondly, the geographical identifier in the supplied data is given by the municipality, not on the household level. Thus, when using the spatial dimension as exogenous

variation, the analysis is restricted to the municipality unless we are willing to make assumptions on the how households are distributed within municipalities. Besides decreasing the sample size, a municipality-level limitation does not intefere with the task of identifying the causal relationship of the overall municipality effect. However, the direct effect on household level will be unidentified without further assumption. When we use household level data, we assume that all households in a municipality are located at the centroid of the municipality. This assumption can be seen as meassurement error possibly introducing biased in our results. In the following analysis we will abstact from this potential source of bias.

3. Finally, note that the burglary measures available are not comparable across the two data sets, VMR and ERV. Specifically, the ERV data sets do not provide observations on burglary attempts and the burglary variable is defined by burglary incidences in the past 5 years, whereas the VMR provide this variable for a time horizon of 12 months. Therefore, municipality-specific effects are not easily removed by comparing the measured burglary victimisation in the two data sets.

4 Shutter Usage and Burglary Victimization

In this section, we explore the relationship between shutter usage and burglary victimization using simple linear probability models. As also noted in Vollaard and Koning (2009), the linear probability model is a convenient approximation to modeling the binary response variable; we also apply probit models in which we find similar results. This exercise sheds light on the correlation between these variables and why it is challenging to establish causal effects.

4.1 A Naive Approach

We are interested in estimating the causal effect of crime preventive window shutters on burglaries and burglary attempt. As a first naive approach to estimate the effect, we run the following regression at the municipality level:

$$y_i = \alpha + \beta_1 S_i + \beta_2 X_i + \epsilon_i, \tag{1}$$

where y_i is the fraction of respondents having experienced burglary or attempted burglary; S_i is the fraction of households with shutters installed; and X_i is a set of municipality controls. Results are depicted in the following table. Puzzling, we find that the use of shutters actually increases the fraction of households having experienced burglary or burglary attempt. This illustrates the importance of considering how to interpret results and to think carefully about the difference between correlation and causality. Although the use of shutters might decrease

Table 1: Naive regression

	(1) Burglary and attempts	(2) Burglary and attempts
Shutters	0.00794	0.0115
	(0.54)	(0.80)
Controls	Yes	No
Observations	443	443

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Burglary victim regressions

	(1) South	(2) South	(3) North	(4) North
Shutter	0.00384	-0.0100	-0.0561*	-0.0539
	(0.13)	(-0.33)	(-2.01)	(-1.93)
Controls	No	Yes	No	Yes
Observations	136	136	307	307

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the crime level it is also possible that a higher crime level increases the incentive for households to invest in window shutters. The problem of relying on the regression in (1) is that of **reversed causality.**

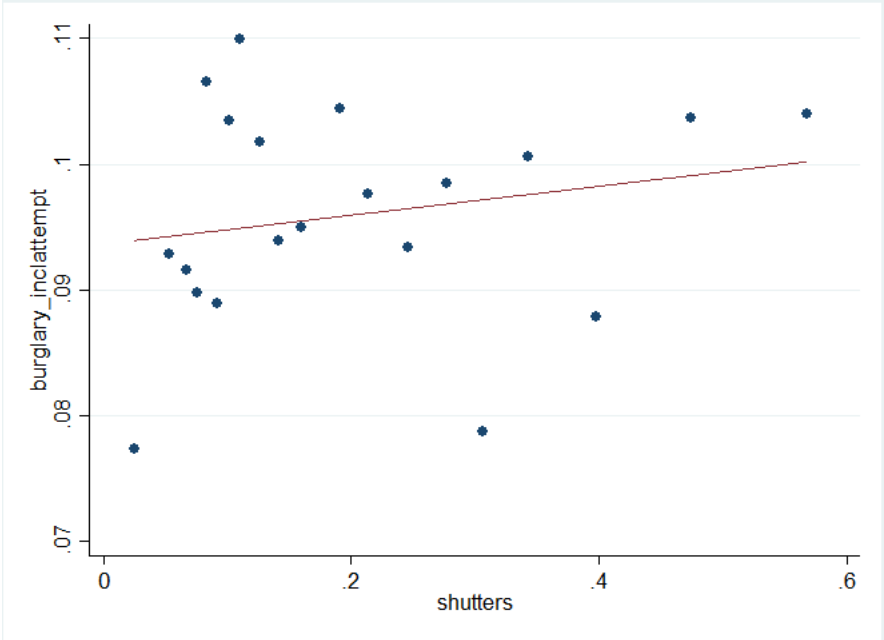
At this stage, however, it is useful to understand if there is any correlation between the two. Figure 5 shows a binned scatterplot of the shutter adoption rate and the fraction of households that have experienced burglary victimisation on the municipality level. Therefore, it is crucial to find a source of exogenous variation in order to estimate the causal effect.

4.1.1 Heterogeneity effects due to the spread of shutters.

It has previously been stated that precationary devises might have a displacement effect meaning that installing devise could lead criminals to your neighbors instead. One could easily imagine that the direct effect of installing window shutters depends on whether your neigbors allready has shutters and hence the alternative opportunities of the burglars. For a quick glance at such effects we regress burglary rates on shutter installment rates at the municipality level dividing the country in North(north of the rivers) and South, since we know that the adaption of shutters is much larger in the south.

Table 2 shows that the correlation is negative and less ambigous in the north. Meaning

Figure 5: Binned Scatterplot



that the overall effects (municipality level) of shutter installations are higher in a low adaption environment. This is somewhat pussling. It it not clear that the adaption environment would matter at all for the overall effect. And one could also imagine an opposite effect where burglaries on aggragated level would drop faster once a municipality is approaching full saturation and limiting the options for burglars dratically.

4.2 Controlling for Municipality Fixed Effects

In principle it is possible to utilize time variation in the use of shutters to uncover the causal effect by estimating the change in burglary victimisation on the difference in shutter usage. We control for fixed effects at the municipality level. Unfortunately, as noted in Section 3, the ERV data only contains information on burglaries and not burglary attempts. Also, the burglary variable is not measured in the same way in the ERV and VMR data sets. However, for illustrative purposes we run the following regression and compare it to the naive regression wihtout any controls[1].

$$\Delta y_i = \alpha + \beta_1 \Delta \mathrm{S} + \epsilon_i \tag{2}$$

[1]The same set of controls will be used throughout the paper. The controls include: Dummy for Male respondent, higher education, social benefit as most important income, bottom of the incom distribution, contact with neighbors, avoid places, doorlocks, outdoorlights, car alarm, visibility of colpice in the street. When estimating regressions at the municipality level, these dummies will be sample averages.

Table 3: FD regression

	(1) Cross Section	(2) FD
Shutters	-0.00572	
	(-0.63)	
Difference in fraction with shutters		0.0200
		(0.31)
Observations	423	423

t statistics in parentheses

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

We find that the cross-sectional analysis gives a postive estimate on the effect of shutters on crime rates, see Table 3. However, when we control for the time variation the sign of the coefficient estimate is reversed. These results illustrate that these simple regressions are flawed with issues of endogeneity.

5 Regression Discontinuity Design

In this section, we aim at uncovering the causal effect of shutter usage on burglary victimisation. Based on the geographical analysis it seems that there is a discontinuity in the shutter uptake across the large river of Maas. We utilize this discontinuity in a fuzzy regression discontinuity (RD) design to estimate the causal effects of shutter uptake on burglaries and attempted burglaries.

We note that an analysis on the municipality-level data allows us to infer an *overall effect*, whereas individual-level data allows us to analyse *direct effects* as discussed in Section 3.

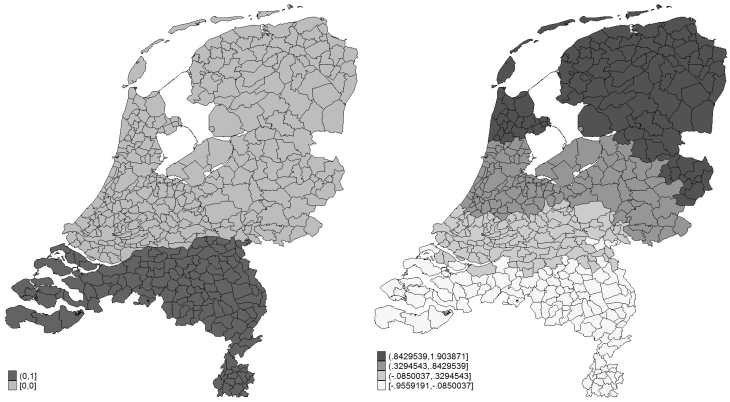
5.1 Augmenting the Data using Google maps

We augment the Dutch crime survey data with the longitude and the latitude of the river Maas. We collect this data from Google maps (maps.google.com) by placing 20 markers in the rivers of Maas and recording the coordinates of each marker. Only datapoints west of Groesbeek (near the German border) are collected because the river bends South from here. With these datapoints, we compute the euclidean distance from the centroids of the municipalities to the nearest point on the river. For municipalities south of the river we encode the distance as negative. Hence our meassure of distance to the Maas will be zero when located at the river. This allows us to use the distance to the river Maas as a running variable in a straightforward RD design. The spread of window shutters also seem to come from the German boarder in the east, with could potentially decrease the power in our instrument.

Therefore we exclude municipalities located to east of the municipality of Amersfort. The distance to the Maas is somewhat complicated by fact that there is another river, the Waal, just north of the Maas. It therefore seem more natural to think of varying adaption of shutters north and south of the river area containing both rivers. As a work aorund we exclude the 14 municipalities (Tussenmaasenwaal) located between the two rivers. With these restrictions, we have a running variable measuring the distance to Maas from a South-Western angle which we'll use in the Rd design. The figure below shows how the instrument varies geographically. The figure on the left simply shows the division according to the river (binary meausre) and the figure on the right shows the running varible measures the euclidian distance to Maas. We'll use the discontinuity in the euclidian distance to Maas in our RD design.

Figure 6: Distance to Maas, (running variable)

(a) Division, River (b) Distance to Maas



5.2 Regression Discontinuity Basics

Since we want to use to a fuzzy RD design to recover the causal effect of shutters on burglaries, we need three basic assumptions:

1. The dependent variable (burglary victiomisation) must be a continuous function of the assignment variable (distance to Maas in this case). We have to be able to model this correctly. We can test this through

   - plots of the dependent variable on the running variable, and
   - testing discontinuities which we do not believed to affect burglaries (for instance distance to some other unrelated point 35 km south of Maas).

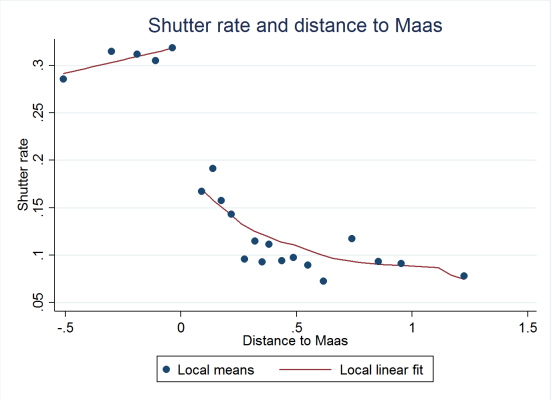
2. Individuals (or municipalities) cannot manipulate the assignment variable.

   Clearly geographical location of rivers is predetermined but the political assignment of municipality borders may not be random. Individuals may move to specific municipalities based on preferences which correlates with confounders (e.g. a preference for living on the northside of Maas correlated with income). This can be partly tested by looking at the density of individuals. We use municipality level data so this can be tested by looking at population sizes/density in different municipalities.

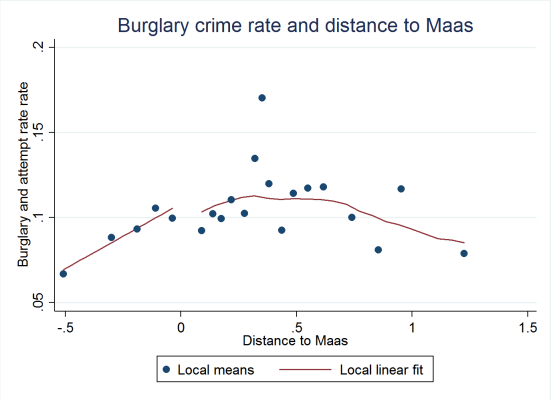
3. There can be no other confounding discontinuities across the river Maas.

Figure 7: Municipality level results

(a) Fraction with shutters



(b) Burglary crime rate



5.3 Municipality level results

Graphical evidence

The graphs below show the main graphical results from our municipality level estimates. The graphs play an important role to guide our decisions on bandwidth and polynomials.

Figure 7a shows the fraction with shutters by the distance to Maas from the south and is a graphical representation of the first-stage (regression equations are discussed below). Each point is a local mean and the overlaid lines are predictions from local linear regressions of the shutter rate onto the distance to Mass (estimated with a rectangular kernel and a bandwidth of 0.5). Figure 7a clearly shows the discontinuity in shutter adoption on either side of the Maas which suggests that the discontinuity around Maas can be used to instrument shutter rate adoption .

Figure 2b is a similar type of plot, but with the burglary rate (incl. attempts) on the y-axis. Figure 2b is a graphical representation of the reduced form stage. The basic message from this figure is that there doesn't seem to be any discontinuity in burglaries and therefore there seems to a zero overall causal effect running from shutters to burglaries

Figure 3a-b depict potential confounders which doesn't reveal any clear discontinuities. The graphs are, however, quite noisy.

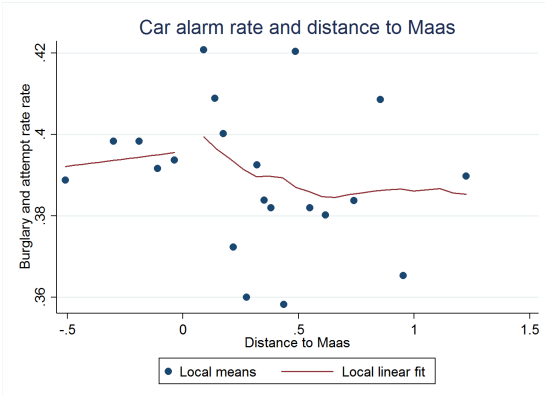
In sum, there is a large discontinuity in shutter adoption around Maas, but no effect on burglaries or other covariates.

Formal method

Next, we carry out the formal part of the analysis, utilizing the discontinuity driven by the river Mass in a regression discontinuity design. Following Hahn, Van Der Klauw and Todd

Figure 8: Municipality level covariate checks

(a) Fraction with car alarms



(b) Share in bottom 20% income

(2001) we run a straightforward 2SLS to estimate the causal effect from our RD strategy. Specifically, we run the following regressions:

$$\mathrm{B}_i = \beta_0 + \beta_1 \mathrm{S}_{it} + \mathrm{X}_{it}\gamma + \mathrm{F}_1(\mathrm{age}_i) + u_{it}$$
$$\mathrm{S}_i = \delta_0 + \delta_1 \mathrm{Z}_{it} + \mathrm{X}_{it}\omega + \mathrm{F}_2(\mathrm{age}_i) + \nu_{it}$$

Where B is the burglary rate, S is the shutter rate and $Z = \mathbf{1}$(above the Maas) is the instrument for the shutter rate and X is a vector of controls:

- If Z only affects shutter adoption (and nothing else), including additional controls decreases standard errors but should not change coefficients.
- If Z affects shutter adoption and some confounding covariates, including these confounding variables as additional controls decreases bias in $\hat{\beta}_1$ (because we then control for the effect which runs through the confounders)

F has to sufficiently flexible to be able to capture the smooth nature of the burglary rate (absent of the discontinuity of course). As we saw in the graphical presentation, the burglary rate is quite "jumpy"/difficult to model. To avoid relying on stark functional form assumptions and/or high degree polynomials we resort to semiparametric models. To be precise, we run local 2SLS models, thereby only estimating the causal effect off the municipalities close to the Mass boundary. The results will shows that even with the semiparametric models, it is difficult to model the "jumpy" burglary rate with a sufficient degree of robustness. We specify F to be linear on each side of the threshold (The river Mass is the threshold), but we also run the models with a linear term which does not vary across the threshold. Allowing trends to vary across the threshold in RD design is generally the preferred method, as we want to allow for as much flexibility as possible.

In practice we estimate the models with the rectangular kernel (kernel choice is usually quite innocent, see Lee and Lemieux (2010)). Since bandwidth choice is usually important and we will therefore run regressions using other bandwidths assessing the robustness of our results wrt. bandwidth.

Given assumptions mentioned in previous subsection, $\hat{\beta}_1$ is the causal estimate of the shutter rate on crime. In the municipality level analysis $\hat{\beta}_1$ is the causal effect on overall crime

Results

The table below shows the estimation results from our RD strategy on the municipality level. The RD columns contain estimates using a bandwidth of 1. This is a rather wide bandwidth (we'll see later that bandwidth matter quite a lot) but this is necessary to have enough power.

The first column contains the simple OLS, regressing municipality level of burglary victimization on the fraction of shutters. The negative estimate implies that an increased use of shutter will decrease burglary victimization. The fuzzy RD estimates are depicted in columns 2-5 (instrumenting the fraction of shutters with whether the municipality is located above the river of Maas) we find zero effect of shutters. The first stage F-stat shows that the river instrument works well and there is enough power to rule out weak instrument issues. In columns 2 and 3, we allow for different linear trends in crime rates on both sides of the river. The results does not change when we control for other municipality characteristics, as the fraction of household in the lowest 22 pct of the income distribution and visibility of the police in the street, in RD(2). The zero result is robust to different functional form assumptions, estimated with a globally linear function in RD(3) and RD(4).

Table 4: Municipality level regression results

	(1)	(2)	(3)	(4)	(5)
	OLS	RD	RD	RD	RD_global_2
Effect of shutters	-0.0590*	0.0522	0.0613	-0.0484	-0.0509
	(-2.25)	(0.65)	(0.75)	(-0.60)	(-0.61)
Controls	No	No	Yes	No	Yes
First stage F-stat		51.85	48.12	49.55	45.00
Observations	216	205	205	205	205

t statistics in parentheses

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

Formal evidence individual level

We now move onto the household level analysis. This allows us to control for characteristics on the household level and increases the number of observations dramatically. In the analysis on the household level we estimate models that are equivalent to those estimated on the municipality level. However, we decrease the bandwidth to 0.5 to increase flexibility. The bandwidth decrease does not cause power issues in the household level regression, because we have plente of observations here. We will see that results are extremely dependent on bandwith choice

The table just below presents the main results of the household level analysis and the table after that checks for robustness with respect to bandwidth choice. The tables shows:

- Main table: The river instrument works ekstremely well. We have huge F-stats and no weak instrument issues. This was also clearly visible in the graphical analysis. The estimates in the main regression table *seem* to suggest that shutters have a positive causal effect on burglary victimization risk. This contrasts the theoretical idea that shutters should decrease crime victimization risk. However, we note that the bandwidth can be flawed.

- Bandwidth table: Estimates from the regressions correspond to column 3 in the main household level table, but the bandwidths are varied from 0.2 (narrow) to 0.8 (wide). We see that the results vary substantially with the choice of bandwidth; this should cause worry.

There is an implicit bias/variance tradeoff when bandwidth is selected:

- Narrowing the bandwidth decreases bias but increases variance.

- Widening the bandwidth increases bias but decreases variance. Cross-validated bandwidths or using Silverman's rule of thumb bandwidth <u>does not</u> make the results less dependent on bandwidth. These procedures may help guide the econometrician in the most efficiengt bias/variance tradeoff. However, the results are going to be non-robust wrt. bandwidth anyway.

Our conclusion is that the results are extremely non-robust with respect to bandwidth. We cannot see any credible effects of burglary victimization. Guided by our graphical analysis, there seem to be little evidence for any causal effects of shutters on the risk of burglary victimization. However, there is a great geographical divide in the shutter adoptation rate across the river Maas.

Table 5: Household level regression results

	(1)	(2)	(3)	(4)	(5)
	OLS	RD	RD	RD	RD
Effect of shutters	-0.00727	0.356**	0.324**	0.274*	0.252*
	(-1.46)	(2.88)	(2.60)	(2.30)	(2.10)
Controls	No	No	Yes	No	Yes
First stage F-stat		62.53	60.22	63.99	61.87
Observations	33915	19706	19706	19706	19706

t statistics in parentheses

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

Table 6: Bandwidth robustness

	(1)	(2)	(3)	(4)	(5)
Bandwidth	0.2	0.4	0.5	0.6	0.8
Effect of shutters	1.535	0.492**	0.324**	0.0690	0.0738
	(1.71)	(3.04)	(2.60)	(1.14)	(1.26)
Controls	Yes	Yes	Yes	Yes	Yes
First stage F-stat	3.822	40.67	60.22	240.7	261.5
Observations	8274	16312	19706	31129	33225

t statistics in parentheses

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

6 Heterogeneity in the Causal Impact of Shutters

Despite finding zero effects from installation of shutters using a credible instrument, we now turn to exploring how the causal effect of shutters varies by the adaption level across municipality. It could be possible that the zero effect on individual level actually masks strong heterogeneus effects across municipalites with few and many shutters installed. We imagine that the share of households in a municipality with shutters installed can have ambigous effects for the individual:

- Effects **increasing** in the share of shutters installed: Consider a municipality where everyone has shutters installed except one household. This household is facing a high risk since everyone else have adapted cautions behavior, hence shutter installation would bring a large reduction in burglary risk.

- Effects **decreasing** in the share of shutters installed: Can be explained by the share of shutters bringing down the general risk of burglary hence lowering the advantage of installing shutters in a particular household. This effect could potentially operate through several different channels. Overall crime level falling, criminals substituting to other types of crime (eg. car theft) or local burglars substituting geographically to other municipalities.

A simple way of exploring heterogeneity in the effect of shutter usage on burglary victimisation is obtained by incorporating interaction terms between the indicator of a households installation of shutters and the share of households with shutters installed in the municipality (calculated as leave-one-out, $-i$). The following regression at the household level shows this approach:

$$y_i = \alpha + \beta_1 S_i + \beta_2 S_i \bar{S}_{j,-i} + \beta_3 \bar{S}_{j,-i} + \beta_4 X_i + \varepsilon_i,$$

where subscript i denote a particular household in municipality j and $\bar{S}_{j,-i}$ denotes the shutter adoption rate in municipality j averaged across all households in the municipality apart from household i. The remaining variables are defined previously.

The equation suffers from the same endogeneity problems as seen in Section 5. As we are interested in estimating coefficients$\beta_1$and $\beta_2$we will instrument the vector $(S_i, S_i\bar{S}_{j,-i})'$with our geographical discontinuety. Hence our instrument vector for the RD will consist of our instrument from Section 5 and the instrument interacted with the share, $(Z, Z * \bar{S}_{j,-i})'$.

	(1) OLS	(2) RD	(3) RD	(4) RD	(5) RD	(6) RD
Shutters	0.00633	0.00772	2.476	1.746*	2.039	1.480
	(0.68)	(0.83)	(1.71)	(1.99)	(1.71)	(1.92)
Shutters x saturation	-0.0252	-0.0301	0.314	-0.244	0.0544	-0.374
	(-0.67)	(-0.80)	(0.40)	(-0.43)	(0.09)	(-0.80)
Controls	No	Yes	No	Yes	No	Yes
First stage F-stat			1.746	2.629	1.771	2.735
Observations	33915	33915	19706	19706	19706	19706

t statistics in parentheses

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

Table 7: Heterogeneity in installment shares

Table **??**shows our results. We do not find any indication of significant heterogeneus effects. And our previous results of zero effects maintain.

7 Conclusion

In this paper, we have studied the causal effect of installing roll-down window shutters on burglary victimization. This question is of particular interest within the large literature trying to estimate how crime preventive behavior affects the crime level. However, identifying the causal effect of shutters on crime is associated with great difficulties. It is possible that households install shutters as a reaction to burglary victimisation rather than the other way around. Also, the correlation may be driven by unobserved confounders. Naive results suggest that installing shutters actually increases the probability of being a victim of burglary. We overcome this challenge by setting up a quasi-experimental fuzzy regression discontinuity design to investigate the causal effect of shutters on burglary victimization. We instrument the decision to invest i shutters with distance to the large River of Maas. Thus, we treat the geographical patterns in the shutter adoption rate as exogenous. We find this, to be a very strong instrument. We find **no** evidence that suggest a causal relationship between shutter investment and burglary victimisation. In our RD setup, we do find a small positive significant result when estimating the effect of shutters on burglary victimization at the individual level - however, this result by no means robust to the bandwith level. Therefore, we do interpret that result in any causal matter.

We suspect that the our findings of zero effect reflects the existence of heterogenous effects, that could cancel each other and thereby give us insignificant results. It could be that the effect of installing shutters in a municipality with a high shutter rated differed from the effect

of installing shutters in a municipality with a low shutter rate.

In conclusion, we do not find evidence for any causal effect of shutters on burglary rate. The drop in crime and burglary victimization rates over the last few decades remains a puzzle.

7.1 Further Research

We have conducted this analysis under strict time limitations. With more time available, we suggest incorporating spatial considerations into the present analysis. We find the following extensions particular interesting for further research:

- *Accounting for the 'copying effect' hypothesis in the causal* estimate*:* It was established in yesterday's analysis that there is social contagion in shutter adoption. The causal effect of shutter adoption on burglary victimisation may be more exaggerated by this behaviour. In particular, we conjecture that the effect might not be limited to

  $$\text{Shutter adoption} \rightarrow \text{Burglary victimisation}$$

  but rather enlargened by a more complicated mechanism:

  $$\begin{array}{ccccccc} \text{Shutter adoption} & \rightarrow & \text{Burglary victimisation} & & & & \\ & \searrow & & & & & \\ & & & \text{Shutter adoption} & \rightarrow & \text{Burglary victimisation} & \\ & & & & \searrow & & \\ & & & & & & \ddots \end{array}$$

  This phenomenon is easily modelled with household-level data in a spatial lag model on which we can impose the RD design for establishing the causal effect of interest.

- *Studying spatial heterogeneity through spatial dependence*: The heterogeneity in the causal effect of shutter adoption on burglary victimisation can also be modelled in a spatial error model. In particular, consider the case where heterogeneity is driven in the constant β_0 of

  $$y_i = \beta_0 + \beta_1 S_i + \beta_2 X_i + \varepsilon_i.$$

  Then, assuming that β_0 is independent of X_i, we can model the heterogeneity by assigning spatial dependence:

  $$\beta_0 = \rho W \beta_0 + \eta \quad \Leftrightarrow \quad \beta_0 = (I_n - \rho W)^{-1}\eta$$

where W is the spatial weight matrix. Combining these equations, we get the spatial error model:

$$y = (I_n - \rho W)^{-1}\eta + \beta_1 S + \beta_2 X + \varepsilon.$$

References

Vollaard, Ben and Pierre Koning. 2009. "The effect of police on crime, disorder and victim precaution. Evidence from a Dutch victimization survey." *International Review of Law and Economics* 29 (4):336–348.