Geographic Patterns in Crime Precaution: the Case of Window Shutters in the Netherlands

Team 2

April 6, 2017

Abstract

We present a model and empirical analysis of the hypothesis that social contagion affects the adoption rates of crime precaution technologies. In a model of investment choice, the primary channel is that a household's decision to invest in costly and observable crime deterrents is affected by its neighbors' decisions as well. We focus on the particular technology of window shutters and verify that there is a high degree of spacial auto-correlation in the distribution of technology uptake. We explore other covariates and show that spatial spillovers are the most salient predictor for uptake, more so than individual characteristics. The IV result using a SARAR model is consistent with the Probit estimation results. Finally, we predict the rate and saturation levels of uptake in the Netherlands using the initial distribution of shutter uptake, and find that saturation will occur in around 2075 at roughly 40% adoption within each municipality.

Contents

1 Introduction

Societies and individuals invest significant time and capital into crime deterrence, where private expenditure can even outpace public expenditure (Shavell, 2015). Separately, there has been a marked decline in the rates of crime throughout the developed world since the 1980s, which has been the subject of many studies, including Donohue and Levitt (2008) and Colen et al. (2016). One of the salient explanations for the decline in crime rates is the adoption of crime-preventing technologies such as more secure windows in houses and engine immobilisers in cars (Vollaard and van Ours, 2011; van Ours and Vollaard, 2016). These papers exploit exogenous policy regime changes where consumers either do not have a choice (in the case of house protections) or do not realize they have a choice (in the case of engine immobilisers) over the level of crime prevention technologies they adopt.

This paper explores mechanisms governing household adoption of a particular crime-precaution technology, the roll-down window shutter. These externally mounted metal shutters provide very high levels of protection against burglaries since they are very difficult to remove or penetrate, and they completely cover the most obvious weakness of windows: the glass itself. They are very clearly visible, fairly costly, and once installed, permanent. Therefore this precaution investment is unlikely to be made lightly, and it provides the laboratory for testing models of adopting precautionary technology.

There is large geographical variation in the prevalence of window shutters in the Netherlands, which makes it possible to test a social contagion model of adoption. Window shutters are more common in southern Europe than in northern Europe, and although in the Netherlands there has been a steady rise in the prevalence of window shutters from the 1990s until today, it is still much higher in the south near the Belgian border. The clear “origin" to the technology adoption makes it likely that the prevalence of window shutters will spread from south to north over time.

This paper presents a model of individual choice over adopting precautionary investments, and it tests this model using survey data from the Netherlands that sampled over two periods with roughly 75,000 households sampled in total. These data provide a wide range of demographic details and household views on crime and safety in addition to measures of precautionary technology adoption.

Empirically, we show that there is large spatial auto-correlation as measured by Moran’s I, which makes standard Ordinary Least Squares methods highly biased. Instead, we estimate a spatial lags model using various weight matrices that account for the nature of the spillovers. In addition to weight matrices that account for influences from all neighbors, we create a weight matrix that is only influenced by neighbors to the south, which accounts for the idea that the presence of a new technology may be more influential than its absence. We also include economic weights in addition to geographic weights, which intuitively captures the idea that neighbors that are more similar in terms of observables are more influential than neighbors that are less similar, holding constant geographical distance. This innovation captures the patterns shown in empirical evidence that individuals in the same income groups are more likely to consume similar bundles of goods. Finally, we deal with the inherent endogeneity in spatial dependency models by estimating an IV spatial regression using spatially lagged explanatory variables.

In the final part of the paper, we estimate a prediction model that projects the rates and timing of saturation in shutter adoption in the Netherlands using the earlier set of surveys as a baseline. We find that the maximum rate of adoption within a municipality is around 40%, and that the process of saturation will take 70 years from the time of the 2005 survey.

The paper proceeds as follows: Section 2 introduces a model of social contagion in the individual choice over adopting window shutters. Section 3 describes the data used in our analysis, and it describes the methodology used to aggregate individual-level survey results to municipality-level measurements. Empirical analyses conducted with municipalities as observations use these reweighted variables. Section 4 provides empirical evidence that there is significant spatial autocorrelation in the patterns of crime prevention technology adoption and presents the spatial dependency model. We estimate both Probit and IV specifications. We also provide a prediction model of saturation over time across the Netherlands. Section 5 discusses the limitations of our empirical strategies, and section 6 concludes.

2 Modeling Spillovers and Social Contagion

Our empirical analysis is guided by a model of individual choice over investment in crime precaution technologies in the presence of social contagion in adoption behaviors. The model is broadly based on Shavell (1991), focusing primarily on investments in "observable precaution," those that are visible to individuals not in the household. We explicitly model two additional facets of the choice that have been hypothesized to be relevant: the possibility that individuals experience an idiosyncratic shock that induces them to invest more (such as being the victim of a crime), and the social contagion channel that they are more likely to adopt precautionary measures if those around them do. There are many potential ways to micro-found social contagion, but we model the choice as purely an investment in crime-deterrence.

As in the original Shavell (1991) model, the goal of a potential victim is to minimize the expected value of the amount stolen plus the cost of precaution technologies. Households have identical preferences and are risk-neutral. They decide whether to adopt shutters as an *observable* safety precaution against being a victim of theft. The observability of shutters relative to other unobservable precautions such as locks and burglar alarms is important for signaling to potential thieves and neighbors that a household is particularly protected against burglary. For simplicity of notation, individual subscripts are suppressed.

- S is an individual's indicator variable for adopting shutters while $\bar{S}_a$ is the average adoption in the geographical area, $\bar{S}_a \in [0, 1]$, and P_s is the price of shutters
- $x = [x_1, ...x_s, ...x_N]$ is a vector representing the total amount of investment in N possible safety precautions indexed by i, $x \geq 0$. Recall we are particularly interested in x_s, representing shutter prevalence
- y is household income
- $s(x, y)$ is the amount stolen if a thief enters a household, where $s(x, y) \geq 0$, $\frac{\partial s}{\partial x_i} < 0 \forall i$, $\frac{\partial^2 s}{\partial x_i^2} > 0 \forall i$, $\frac{\partial s}{\partial y} > 0$, $\frac{\partial^2 s}{\partial y^2} < 0$

The choice to adopt shutters is increasing in household income and decreasing in the amount of investment in other precautions such as outdoor lights and better locks on doors. Note that we intentionally do not specify the sign of the cross partial $\frac{\partial^2 s}{\partial x_s x_{-s}}$, which determines whether adopting shutters x_s tend to be complements or substitutes for other precautionary measures x_{-s}. This is an empirical question that we explore in our subsequent analysis.

Let $p(entry)$ be the probability that a household will be entered by a thief. It is lowered by the presence of observable precautions, in this case shutters. Therefore

$$p(entry|S = 1) < p(entry|S = 0)$$

Conditional on not having shutters, the probability of being a victim of theft is raised by the average shutter saturation in the neighborhood:

$$p(entry|S = 0, \bar{S}_a = low) < p(entry|S = 0, \bar{S}_a = high)$$

Intuitively, if an individual's neighbors become observably better protected, it is more likely thieves will target the less protected houses. At the extreme ends of the saturation distribution, when $\bar{S}_a = 0$ and $\bar{S}_a = 1$, the probability of entry is the same for all households. Allowing the average adoption rates of shutters in the geographical area to influence the probability that a household will be entered is the channel for social contagion.

The social contagion model can be enhanced with idiosyncratic shocks ε that capture personal preferences regarding safety. These shocks can be positive (an extra preference for precaution due to past history with crime) or negative (a lower preference due to personally feeling safe or trusting the police). In this case, the *perceived* probability of entry is also a function of personal shocks.

The household therefore chooses to adopt shutters if the expected loss from adopting shutters is less than the expected loss without shutters[1]. It evaluates the expected loss from burglary as the product of the probability of being entered and the amount stolen, taking its household income y, previous investments x, and idiosyncratic shocks ε as given. Most importantly, it evaluates the decision in response to the adoption levels by its neighbors $\bar{S}_a$.

$$p(entry|\bar{S}_a, \varepsilon, x, S = 1) * s(x, y) + P_s < p(entry|\bar{S}_a, \varepsilon, x, S = 0) * s(x, y) \quad (1)$$

This choice is presented as a static one, but it is easy to imagine that it is a choice that households make every period. In that case, the initial distribution of shutter adoption can have a large impact on the adoption rates across a region over time.

The specific hypotheses that we test are the following:

1. Proximity to areas of high shutter adoption will raise the probability of adoption

2. Higher household income will raise the probability of adoption

3. Idiosyncratic histories and views that make individuals feel less safe will raise the probability of adoption for shutters.

4. Higher investment in other precaution technologies has an ambiguous effect on the probability of shutter adoption; this is a question we examine empirically in the subsequent sections to determine the substitutability or complementarity between shutter adoption and other investment.

The next section describes the data and explains the variables we use to test these hypotheses.

[1] The price of unobservable precautions is set as the numeraire

3 Data

The data come from several surveys of households in the Netherlands conducted over two periods, 1993-1995 and 2005-2008. The surveys are representative at a national level and are treated as two cross-sections in our analysis. The main topics of the survey are individuals' views on crime and safety, personal history with crime vicitimization, adoption of crime-deterring investments, and demographic variables.

3.1 Control variables

In the main regressions below, we include a range of control variables based on individual responses to the national crime surveys. For municipality-level regressions, these survey responses are aggregated by age group and reweighted to be representative of the true age structure of the municipality, as described in Section 3.2 below.

We include the ethnic origin (native, Western immigrant, Non-Western immigrant) as an indicator of local diversity, which may affect social cohesion and trust (e.g. Putnam (2007)), although there is disagreement on whether this effect exists in Europe (Gesthuizen et al., 2009). Moreover, higher education levels, and whether the main household income source is benefits or wage earnings, as well as household income categories are included as proxies for socio-economic status; the age structure is included because there is some evidence that age correlates with fear of crime (Mark, 1984; Ortega and Myles, 1987). We also use an index of neighborhood perceptions (incl. cohesion, friendliness etc.), and an index of satisfaction with police effectiveness, either of which may represent alternative ways of insuring against crime risk; perceptions of safety outdoors and at home, and a history of victimization in the last 5 years, are included as measures of the perceived benefit of crime precautions. These variables capture y and ε in the model.

3.2 Reweighting survey results by demographic characteristics

To obtain the average shutter prevalence for each municipality, we can aggregate the individual-level survey data into shutter prevalence for each of the 4 age-groups described in the previous section for each municipality, and then take a weighted average of shutter prevalence based on the distribution of age-groups within the municipality. However, because the survey is representative at the national level, but not necessarily at the municipality level, we need to reweight each age-group's shutter prevalence by the true distribution of age-groups for each municipality rather than weighting shutter prevalence by the distribution of age-groups implied by the survey responses for each municipality.

To clarify this reweighting process, consider a simple example in which shutter prevalence in a particular municipality is 15% among survey respondents younger than 45 and 35% among survey respondents 45 or older, and that the crime survey has an equal number of respondents within each of these age groups for this municipality. Without any reweighting, we would calculate this municipality's average shutter prevalence as $15\% * (.5) + 35\% * (.5) = 25\%$. However, if this municipality's true proportion of homeowners younger than 45 is 25% and its true proportion of homeowners older than 45 is 75%, then the municipality's true average shutter prevalence is $15\% * (.2) + 35\% * (.8) = 30\%$. Mathematically, we can summarize this reweighting procedure to calculate average shutter prevalence for each municipality m as:

$$E[S_m] = \sum_{i=1}^{4} E[S_m|A_i] \cdot P(A_{im}), \tag{2}$$

where $E[S_m]$ is defined as average shutter prevalence for municipality m that we are trying to calculate, and $E[S_m|A_i]$ is the shutter prevalence for age-group i within municipality m obtained from aggregating individual-level survey data. The 2008 Dutch shape file (gem_2008_gn3_WGS84) contains the true proportion of homeowners within each age-group i for each municipality m, defined as $P(A_{im})$ in Equation 2. Thus, after aggregating the survey respondents' shutter prevalence by age-group for each municipality, we use the true proportions from the shape file to calculate each municipality's average shutter prevalence using the reweighting procedure described above [2].

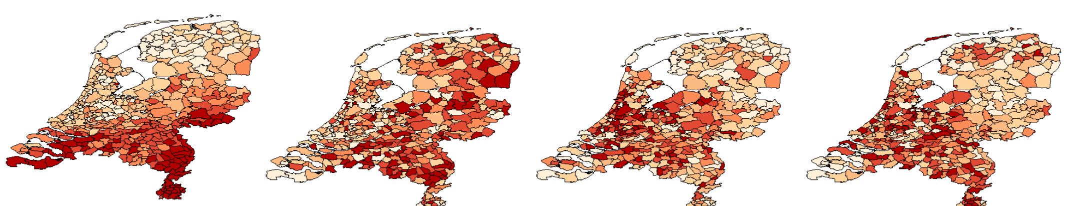
In addition to using this reweighting procedure to calculate average shutter prevalence by municipality, we use this same reweighting procedure to calculate average prevalence of all precautionary variables of interest (e.g. outdoor lights, door locks, burglar alarms). Furthermore, we use the same reweighting procedure described above to calculate municipality averages of the control variables described in Section 3.1 for our municipality-level analysis.

4 Empirical Analysis

4.1 Patterns of Crime Precautions in The Netherlands

The model of spillovers described in section 2 above suggests that the use of shutters will spread outward from an initial hotbed. In this case, a likely hotbed is Belgium, where the use of rolldown shutters is particularly high. As an initial assessment of this hypothesis, we mapped the percent of the population that uses rolldown shutters and other precautionary measures in each municipality. These results are displayed in Figure 3 below.

Figure 1: Plots of Precautionary Measure Prevalence by Municipality



(a) Rolldown Shutters (b) Outdoor Lights (c) Door Locks (d) Burglar Alarms

Notes: Prevalence rates are divided into six quantiles. Darker colors indicate higher prevalence rates.

Consistent with a contagion model spreading from Belgium, these figures clearly show much higher prevalence rates of roll-down shutters among municipalities near the Belgian boarder (i.e., southern municipalities). Furthermore, the prevalence of other precautionary measures such as door locks, outdoor lights, and burglar alarms show less clustering overall and specifically less

[2] Technically the shape file also provides the true proportion of people in the municipality younger than 15, but we will assume for simplicity that this younger group does not own homes, so we simply reweight the proportions of the 4 older age-groups described above so that they sum to 1 for each municipality.

clustering near Belgium, which is consistent with our model of crime precaution contagion. That is, shutters spread in a directed manner between spatially contiguous municipalities because they are *highly observable* and the geographic variation results from the fact that shutter prevalence is not yet *saturated*. These conditions are not fully met for the other crime precaution measures that are shown on the maps: enhanced door locks and installed burglar alarms are less easily observed than rolldown shutters simply due to their physical lack of visible features. In the context of our model, this means that the signal of what $\bar{S}_a$is - the observed neighborhood prevalence of crime precautions - is hard to observe. As a result, the contagion effect is less operational.

At the same time,Table 1 shows that outdoor lights and door locks are already highly prevalent in the entire country. In fact, at rates of 85.3% prevalence for each of these measures, they are likely close to saturation in most municipalities. If most municipalities already transitioned to a higher steady state of these precautionary measures, we would not expect to observe the transitional contagion pattern anymore.

Table 1: National prevalence of crime precautions 2005-2008

	Shutters	*Burglar alarm*	*Outdoor light*	*Door locks*
2005-2008	18.5%	12.9%	85.3%	85.3%
1993-1995	10.3%	5.9%	67.4%	75.1%

Source: Dutch national crime survey data. Data shown are % of respondents in a nationally representative sample, pooling all respondents over the stated survey years.

As a descriptive exercise to roughly quantify how proximity to the Belgian border is correlated with the prevalence of various precautionary measures, we use simple linear probability models. In these models, we regress, for example, rolldown shutter prevalence on various individual-level controls (described above in Section 3) and the latitude and longitude of the municipality's centroid. One benefit of this analysis is that it accounts for differences in demographic characteristics among municipalities, so that differences in observed prevalence rates at different latitudes are not driven by differences in observable characteristics of the individuals living in each municipality. The results of this analysis are displayed in Table 2. Focusing on the first line, the table shows that municipalities at higher latitudes (i.e., more northern municipalities) are associated with statistically significantly lower prevalence levels for rolldown shutter, outdoor lights, and higher alarms. However, this association is approximately an order of magnitude stronger for rolldown shutters than for the other two.

These simple linear probability models are restrictive in that they impose a fixed structure on the relation between latitude (and longitude) and the prevalence of precautionary measures. To allow location to relate more flexibly to the prevalence of precautionary measures, we instead include municipality level fixed effects. The fixed effects for each municipality are displayed in maps in Figure 2. The fixed effects capture the excess prevalence of each precautionary measure above what would be predicted solely based on the municipality's demographics. Consistent with Figure 3 and the regression results in Table 2, municipality level fixed effects are larger closer to the Belgian border.

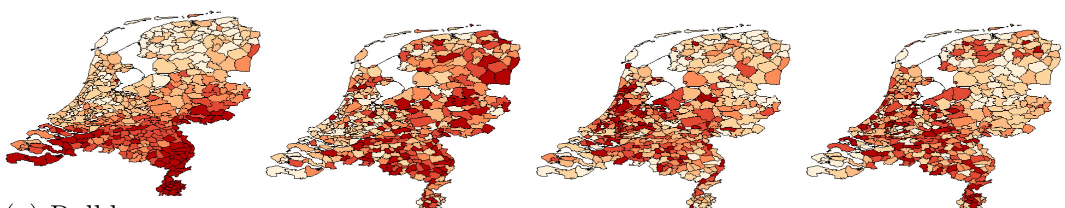
Taken together, these analyses provide suggestive evidence that location is an important

Table 2: Individual-Level Regressions of Precautionary Measure Use on Baselines Covariates and Municipality Location

	Shutters	Door Locks	Outdoor Lights	Burglar Alarms
Latitude	-0.207***	-0.007	-0.032**	-0.014***
	(0.008)	(0.005)	(0.013)	(0.004)
Longitude	0.065***	-0.011***	0.039***	-0.001
	(0.006)	(0.003)	(0.010)	(0.003)
N	64,823	64,823	64,823	64,823
Adjusted R^2	0.093	0.014	0.059	0.015

Standard errors are clustered at the municipality level. All regressions also include individual controls, as described in section 3.

Figure 2: Residual Plots by Municipality



(a) Rolldown Shutters (b) Outdoor Lights (c) Door Locks (d) Burglar Alarms

Notes: Residuals are obtained by including municipality-specific fixed effects in OLS regressions of each precautionary measure on individual level controls (described in the Data section). They are divided into six quantiles. Darker colors indicate larger residuals.

factor determining the prevalence of precautionary measure, particularly in the case of rolldown shutters.

4.2 Test for Tobler's Law

The maps shown in the previous sections suggest that high shutter rate municipalities are more likely to be located in the south, while the north of The Netherlands has lower shutter rates. A related but different question is whether it holds more generally that the pattern of shutter installation rates of neighboring municipalities is related - which would provide preliminary evidence for a contagion model of crime precautions. This hypothesis - that areas are more similar to areas nearby - is sometimes referred to as *Tobler's first law of geography.*

We test Tobler's law by investigating whether the covariance in the variables of interest related to precautions between provinces that are spatially close - as we will define formally - is much larger than covariance between municipalities in general. We test for this spatial autocorrelation using Moran's I statistic (Moran, 1948), which is frequently used in the social contagion literature (see e.g. Case and Katz (1991); Bernasco and Elffers (2010)).

We test for whether the demeaned levels of different precautionary investments y_i show autocorrelation among neighboring provinces. Moran's I statistic for global autocorrelation in this case for the 443 Dutch municipalities is calculated as

$$I = \frac{N}{\sum_{i=1}^{443}\sum_{j=1}^{443} w_{ij}} \frac{\sum_{i=1}^{443}\sum_{j=1}^{443} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{443}\sum_{j=1}^{443} w_{ij}(y_i - \bar{y})^2}$$

where $i, j \in \{1, \ldots, 443\}$, and w_{ij} is a measure of the geographical or social closeness between two municipalities i and j, with $w_{ii} = 0$ by definition (a municipality cannot be its own neighbor).

The pivotal quantity for testing the hypothesis that this statistic is large in a statistical sense is defined by

$$z_I = \frac{I - E(I)}{\sqrt{Var(I)}},$$

where $E(I) = -\frac{1}{443-1}$. This pivot is asymptotically normally distributed.

First, we define the absolute value of the centroid distance between municipalities

$$\Delta c_{ij} = c_i - c_j,$$

where c_i is a 2x1 vector of coordinates. One possible spatial distance weight is then the normalized inverse of this centroid distance:

$$w_{ij} = \frac{\frac{1}{\|\Delta c_{ij}\|}}{\sum_{i=1}^{443}\sum_{j=1}^{443} \frac{1}{\|\Delta c_{ij}\|}}.$$

This weight matrix assigns more influence to municipalities that are closer neighbors than those that are farther away.

The value of Moran's I and the test statistic that result for the demeaned prevalences of precautionary investments by municipality are shown in row 1 of Table 3. We can see that the values for the test statistics are all significantly different from zero. That is, there is strong evidence that there is autocorrelation of shutter prevalences and other precautions among municipalities that are spatially close.

However, some of this autocorrelation may simply result from the fact that proximate municipalities share demographic and other characteristics and that these are driving the autocorrelation. In order to see whether this is the case, we run a simple OLS regression of precaution investment rates on a vector of observable municipality characteristics X of the form

$$Y_i = X'\beta + \epsilon_i$$

and then test for autocorrelation among the error terms using a Moran's I test statistic similar to the one above, but with

$$I = \frac{N}{\sum_{i=1}^{443}\sum_{j=1}^{443} w_{ij}} \frac{\sum_{i=1}^{443}\sum_{j=1}^{443} w_{ij} e_i e_j}{\sum_{i=1}^{443}\sum_{j=1}^{443} w_{ij} e_i^2}.$$

The results of the OLS regression are shown in the Appendix Table 9. The test statistic for this residual autocorrelation among municipality precaution investment rates is shown in row 2 of Table 3. The remaining columns of Table 3 show whether we see the same pattern of residual autocorrelation for other indicators of investment in crime prevention and precaution among municipalities in mutual proximity. The results show that autocorrelation also remains among

Table 3: Moran's I statistic for autocorrelation in precaution investment among municipalities in spatial proximity

Test variables	*Shutters*	*Burglar alarm*	*Outdoor light*	*Door locks*
Demeaned level	0.294***	0.053***	0.048***	0.075***
	(82.134)	(15.250)	(14.009)	(21.652)
OLS residual	0.221***	0.014***	0.046***	0.018***
	(61.770)	(4.475)	(13.372)	(5.697)

Z-scores in parentheses. Residuals are based on an OLS regression of the dependent variable on municipal averages of ethnic origin, education, welfare recipients, wage earners, marital status, age group, income group, neighborhood feeling, perceived police effectiveness, safety perception at home and in the neighborhood, and crime victimization status. See Table 9 in the Appendix for details. Significance levels: * $p < .1$, ** $p < .05$, *** $p < .01$

other crime precaution investments after controlling for covariates.

As an additional test, we investigate whether the pattern of autocorrelation among neighbors is asymmetric: The South-to-North contagion hypothesis for visible crime prevention suggests that the influence should be stronger towards municipalities that are north of the originating municipality than in the opposite direction.To test this, we can adjust the spatial weights to only reflect influence on municipalities that comes from spatially close neighbors in the south:

$$\hat{w}_{ij} = \frac{\frac{1}{\mathbb{1}[South_{ij}]\cdot\Delta c_{ij}}}{\sum_{i=1}^{443}\sum_{j=1}^{443}\frac{1}{\mathbb{1}[South_{ij}]\cdot\Delta c_{ij}}},$$

where $\mathbb{1}[South_{ij}]$ is an indicator function for municipality j being to the south of i as measured by the centroid coordinate latitudes. The results are shown in Table 4. Comparing the I statistics to those that considered symmetric influences, we can see that the autocorrelation among shutters is of similar size if we restrict spatial proximity influence to come from southward municipalities. It is also interesting that the spatial correlation for the other crime-prevention investments such as burglar alarms and door locks, hardly change between the two weight matrices used. These results provide some support for the hypothesis that high shutter prevalence is spreading in a directed manner from south to north among municipalities.

4.3 Spatial Dependency Model

The previous section has shown that the choice of adopting shutters is not independent across municipalities. There is a high degree of spatial autocorrelation, which makes it necessary to adjust our econometric model to include spatial dependencies. The intuition behind these models is straightforward: an individual's choices are affected by the choices of her neighbors. In the case of shutter adoption, we have hypothesized that the decision to adopt the costly and permanent technology is influenced in part by their perceived local popularity. At the municipality level, the average rate of adoption is affected by the rates in neighboring municipalities. Failing to

Table 4: Moran's I statistic for South-to-North autocorrelation in precaution investment among municipalities in spatial proximity

Test variables	*Shutters*	*Burglar alarm*	*Outdoor light*	*Door locks*
Demeaned level	0.352***	0.102***	0.050***	0.299***
	(54.220)	(15.984)	(8.061)	(46.752)
OLS residual	0.283***	0.014*	0.051***	0.102***
	(43.675)	(2.456)	(8.140)	(16.137)

Z-scores in parentheses. Residuals are based on an OLS regression of the dependent variable on. Significance levels: * $p < .1$, ** $p < .05$, *** $p < .01$

account for the influence of geographically proximate observations leads to biased estimates in the presence of spatial autocorrelation.

4.3.1 Probit specification

In order to obtain a baseline estimate of the "contagion" effect from nearby provinces, we estimate a Probit model at the level of individual households. Using the household level data allows us to control for a richer set of local characteristics, including perceptions of police effectiveness and safety. The Probit model takes the following form for household i in municipality k:

$$Pr(Y_{ik} = 1) = \Phi(\alpha_k + \beta_1' W_k S + \beta_2' X_i) \tag{3}$$

where W is a matrix of spatial weights as above, S is the vector of municipality characteristics, and X_i are characteristics of the individual household's circumstances and neighborhood. As usual, $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution. The advantage of this Probit specification relative to simple OLS is that the normal CDF is naturally limited to the range $[0, 1]$, which corresponds to the range of the probability variable (e.g. $Pr(Shutter_i = 1)$) that we are trying to estimate.

Our model guides the different versions of the weight matrix W that we use. The first model weights neighbors by the inverse of the distance between the municipality's centroid and each other municipality (the "Distance" model). This is a simple diffusion model in which the farther away the neighbors are to the municipality, the less influence they have on the municipality's outcomes. The second model constrains spatial influence to neighbors that directly border the municipality ("Borders" model). Another permutation on both the distance and border weights takes into account the purported geographic origin of the social influence and only accords positive weights to neighbors to the south (Distance-south and Borders-south): the contagion effect is asymmetric in its direction.

The main results of the individual-level probit specification are shown in Table 5 show that there is a high degree of spatial dependency, in which the prevalence of shutters in close geographical proximity have a significant positive influence on the household probability of adopting the shutter technology. The magnitude of this effect is smaller when we only allow southern neighbors to influence the choice, which makes sense given that it disregards any spillover from the north, which is is at the least zero. The effect is also smaller if we constrain the spillovers to direct neighbors–those municipalities that share a border. Again this restriction limits the amount of spatial spillover, thereby reducing the overall effect we measure.

Table 5: Individual-Level Probit Regressions of Shutter Use on Baselines Covariates and Spatially Lagged Shutter Prevalence

	Inverse Distance	Inverse Distance (South Only)	Neighbors	Neighbors (North Only)
Shutters (Spatial Lag)	8.450***	6.882***	3.235***	2.572***
	(0.283)	(0.280)	(0.084)	(0.183)
Income >40K€	0.107***	0.105***	0.101***	0.089**
	(0.033)	(0.034)	(0.033)	(0.035)
Victimized in last 5 yrs	0.001	0.001	0.002	0.008
	(0.038)	(0.038)	(0.038)	(0.037)
Other precautions	0.870***	0.883***	0.880***	0.841***
	(0.059)	(0.057)	(0.056)	(0.061)
N	64,823	64,823	64,823	64,823
Log Likelihood	-2.77e+04	-2.78e+04	-2.75e+04	-2.84e+04

Standard errors are clustered at the municipality level. All regressions also include individual controls, as described in section 3. A table displaying all coefficient are available in the appendix.

The other covariates in the model that we test are income, victimization experiences in the last 5 years, and investment in other crime-prevention technologies. High income, denoted in the survey as greater than \$$40k$ per year has a strongly positive effect on the likelihood of adopting window shutters, as predicted in the model. Victimization has a very minor positive effect on the precaution probability, but it is not statistically different from zero. Investment in other precaution technologies raises the probability of adoption, which suggests that these investments are complements rather than substitutes.The magnitudes of these coefficients show that the spatial spillover is the primary driver of the adoption rate, and is much more important than individual characteristics. This provides strong evidence for the social contagion theory. Other demographic characteristics are reported in the appendix in Table 10.

4.3.2 IV specification

The problem with estimating Equation 3 with Probit MLE is that the dependent variable is simultaneously determined with the spatially lagged variable WS. This is Manski's reflection problem: municipalities influence their neighbors, but the municipality's neighbors also influence it (Manski, 1993). The simultaneity bias can be addressed by using an instrument for the spatial lag variable. The solution proposed by Kelejian and Prucha (1998, 1999) and now generally known as the SARAR model is to instrument for the spatially lagged variable WS with the explanatory variables and their first and second levels of spatial lags: X, WX, W^2X etc. Provided that the explanatory variables X are exogenous, these are valid instruments that can provide an unbiased estimate of WS. The intuition is that the higher order spatial lags of the explanatory variables predict the outcomes in a municipality's neighbors, which then predicts the outcomes in the municipality itself. That is, we are estimating

$$Y_{ik} = \alpha_k + \gamma_1' \hat{W_k S} + \beta_2' X_i$$
$$\hat{W_k S} = \xi_k + \pi_1 X_k + \pi_2 W_k' X_k + \pi_3 (W_k^2)' X_k$$

The requirement that X_k and its spatial lags WX_k, W^2X_k, etc are exogenous is not trivial.

Table 6: Individual-Level IV Regressions of Shutter Use on Baselines Covariates and Spatially Lagged Shutter Prevalence

	Inverse Distance	Inverse Distance (South Only)	Neighbors	Neighbors (North Only)
Shutters (Spatial Lag)	2.394***	1.966***	0.953***	0.716***
	(0.081)	(0.082)	(0.026)	(0.065)
Income >40K€	0.023***	0.021***	0.021***	0.021***
	(0.007)	(0.007)	(0.007)	(0.008)
Victimized in last 5 yrs	0.002	0.002	0.001	0.004
	(0.008)	(0.008)	(0.008)	(0.009)
Other precautions	0.128***	0.131***	0.129***	0.130***
	(0.010)	(0.010)	(0.010)	(0.009)
N	64,823	64,823	64,823	64,823
Adjusted R^2	0.106	0.103	0.114	0.084

Standard errors are clustered at the municipality level. All regressions also include individual controls, as described in section 3. A table displaying all coefficient are available in the appendix.

The survey data only provide contemporary household demographics data, and there is likely a high degree of correlation and simultaneity bias between technology adoption and income levels between geographically proximate municipalities, so that the IV exclusion restriction is likely to fail: $Cov(X_k, Y_ik) \neq 0$ is unlikely to be the case.

We explicitly test this assumption on the primary X_k variables that we include in our main specifications. Table 11 shows the main test statistics of Moran's I statistic for demeaned levels of X_k, using both an inverse distance spatial weighting as well as an inverse distance weighting that only considers influences going south-to-north. The Moran's I statistics are almost universally significant. This means that there is a high degree of spatial autocorrelation among the many explanatory variables. The SARAR model requires that the instruments for S be estimated with exogenous X_k, but the kinds of quasi-experimental instruments predominantly used in this literature, such as historical characteristics, natural resource suitability, or political events, are unfortunately not available in this dataset. However, an important extension of this work would consist in using plausibly exogenous instruments, such as funding shocks for local police departments, proximity to shutter supply chains, or historical variation in the physical housing stock as instruments for shutter prevalence. Therefore, the IV model is estimated to the best of our ability, albeit with weak instruments.

Notwithstanding these limitations, the IV estimation results shown in Table 6 are in line with the Probit results we found earlier: Shutter rates among proximate municipalities affect local shutter rates; higher income has a positively significant effect on shutter rates; and there is evidence of complementarity between other precautions taken by a household and the likelihood of having shutters.

Moreover, these results are robust to limiting the effect direction to be south-to-north and to focusing on direct neighbors - both in general and to the south only - in addition to the inverse distance measure of proximity. However, the effect sizes are less than half as large when we only consider immediate neighbors - which is what we would expect as geographic influence likely diminishes with distance but exposure to visible shutters does stops no less at municipal borders than people do. Moreover, smaller municipalities are more likely to have a centroid point that is closer to other provinces (as it is closer to any border of the municipality) and therefore there may be heterogeneity among provinces in effect sizes, which we are abstracting from in this analysis by presenting only an average coefficient.

Based on these empirical estimates presented here, which supports the theoretical model we proposed, there is some - albeit noisy - evidence that a contagion mechanism may be operating with regard to crime precaution investments.

4.4 Predicting Saturation

We use the growth rates in municipalities between shutter adoption rates in the earlier surveys taken in 1995 relative to those in 2005. The ideal specification would use demographic characteristics in 1995 to predict the growth rate in shutter adoption between 1995 and 2005 that we can specifically attribute to non-demographic factors (i.e. social contagion). Then we would linearly fit those coefficients to the demographic distribution in 2005 to predict shutter uptake in 2015. We would repeat the exercise using 2005 as the "initial" period to predict takeup in 2025, iterating forward until we reach convergence.

The data limitations of the earlier survey makes it impossible to condition the growth rate on most individual demographic characteristics in 1995, so we use the available data to predict 10-year growth in shutter adoption rates. The sample size of the earlier surveys is relatively small, and it is unreasonable to expect that each municipality is properly sampled, so we drop the municipalities that are in the bottom 25%-ile of the distribution of observations per municipality (those with fewer than 8 individuals sampled).

The relationship between the initial rates of shutter adoption in 1995 and the growth rate between 1995 and 2005 are shown in Figure 5. We fit a second order polynomial regression with two specifications:

$$\Delta S_m = \alpha + S_{m,95} + S_{m,95}^2 + \varepsilon_m \tag{4}$$

$$\Delta S_m = \alpha + S_{m,95} + S_{m,95}^2 + \Delta y_m + \varepsilon_m \tag{5}$$

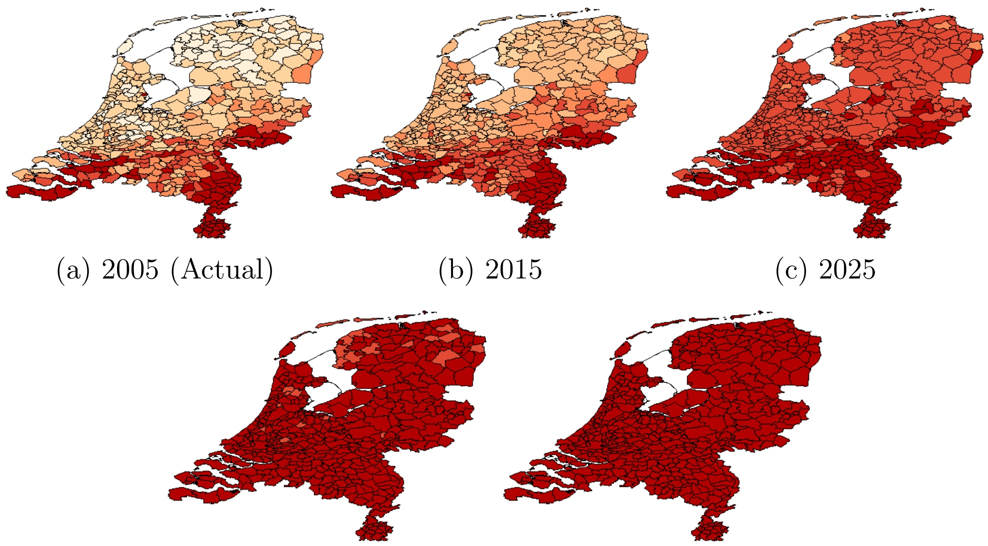
The regression in Equation 5 differs from that in Equation 4 in that it also includes the change in the average proportion of municipality homeowners whose primary income source is labor income. Using the coefficients from this regression (shown in Table 12), we predict future values of shutter adoption at the municipality level using the 2005 distribution of adoption rates.

Based on the coefficients from Equations 4 & 5, we predict that saturation occurs at around 40% adoption rate, which will converge by 2075. The decade-by-decade progression of shutter uptake is shown in Figure 3, and the CDF of the fraction of municipalities reaching convergence by year is shown in Figure 4.

5 Discussion & Limitations

A major limitation of our analysis is that we are trying to model dynamic effects (e.g. the spread of shutter adoption rates over time) without any reliable source of panel or time-series data. Ideally, we would have representative crime survey results over time following the same individuals so that we could properly assess the effects of various channels in affecting precautionary measure prevalence over time with a panel dataset. While we have two separate surveys from 1993-1995 and 2005-2008, the earlier survey has a generally small sample size with very few

Figure 3: Predicted Prevalence of Shutters by Municipality



(a) 2005 (Actual) (b) 2015 (c) 2025

(d) 2055 (e) 2075

Notes: Prevalence rates are divided into six buckets. Darker colors indicate higher prevalence rates.

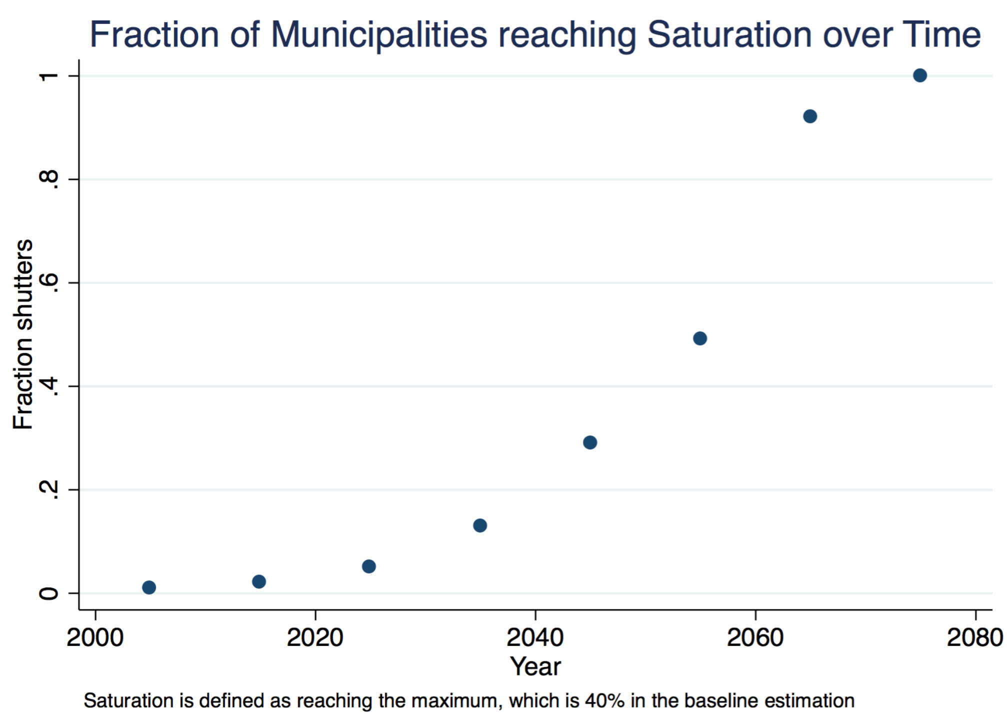


Figure 4

descriptive variables, making it challenging to infer anything regarding social contagion effects from this survey. Furthermore, while the later survey has a very rich set of information, it was administered as a repeated cross-section of survey respondents rather than a panel, meaning that it is inappropriate to infer any changes over time in prevalence rates, demographic changes, safety perceptions, etc. from these survey data. Treating our 2005-2008 data as a static picture of Dutch crime statistics at a point in time still enables us to confidently show the wide variation and substantial spillovers in the distribution of precautionary measure adoption. However, it is particularly difficult to make confident predictions of about future shutter adoption given these the lack of time series data.

6 Conclusion

This paper addressed whether there is evidence that rolldown shutters in The Netherlands are spreading between municipalities following a model of "social contagion". We presented a simple model of social contagion in crime precautions and tested the implications in survey data from a national crime survey. The results show that high shutter rates in a municipality is associated with relatively high shutter rates in "nearby" municipalities. While causality is hard to establish due to data limitations, we show that this pattern of results is robust to controlling for a wide range of covariates, as well as employing a variety of different regression specifications. Our prediction for saturation over time also shows a clear trend spreading from South to North, in line with the predictions of the model.

Further study of the social contagion phenomenon is crucial to accurately assessing the welfare impacts of many public policies. This research suggests that a policy may be able to cover a wide area with limited investment if a local hotbed is established in a well-connected region. Furthermore, it suggests that the impacts of policies may spread well beyond their initial bounds, which can have significant, long-term impacts on both the costs and benefits of policies. This requires additional research on how social contagion spreads behaviors and also which behaviors are likely to be spread via this mechanism.

References

Bernasco, W. and H. Elffers (2010): "Statistical analysis of spatial crime data," in *Handbook of quantitative criminology*, Springer, 699–724.

Case, A. C. and L. F. Katz (1991): "The company you keep: The effects of family and neighborhood on disadvantaged youths," Tech. rep., National Bureau of Economic Research.

Colen, C. G., D. M. Ramey, and C. R. Browning (2016): "Declines in Crime and Teen Childbearing: Identifying Potential Explanations for Contemporaneous Trends," *Journal of Quantitative Criminology*, 32, 397–426.

Donohue, J. J. and S. D. Levitt (2008): "Measurement Error, Legalized Abortion, and the Decline in Crime: A Response to Foote and Goetz," *The Quarterly Journal of Economics*, 123, 425–440.

Gesthuizen, M., T. Van der Meer, and P. Scheepers (2009): "Ethnic diversity and social capital in Europe: tests of Putnam's thesis in European countries," *Scandinavian Political Studies*, 32, 121–142.

Kelejian, H. H. and I. R. Prucha (1998): "A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances," *The Journal of Real Estate Finance and Economics*, 17, 99–121.

——— (1999): "A generalized moments estimator for the autoregressive parameter in a spatial model," *International economic review*, 40, 509–533.

Manski, C. F. (1993): "Identification of endogenous social effects: The reflection problem," *The review of economic studies*, 60, 531–542.

Mark, W. (1984): "Fear of victimization: Why are women and the elderly more afraid?" *Social science quarterly*, 65, 681.

Moran, P. A. (1948): "The interpretation of statistical maps," *Journal of the Royal Statistical Society. Series B (Methodological)*, 10, 243–251.

Ortega, S. T. and J. L. Myles (1987): "Race and gender effects on fear of crime: An interactive model with age," *Criminology*, 25, 133–152.

Putnam, R. D. (2007): "E pluribus unum: Diversity and community in the twenty-first century the 2006 Johan Skytte Prize Lecture," *Scandinavian political studies*, 30, 137–174.

Shavell, S. (2015): "A simple model of optimal deterrence and incapacitation," *International Review of Law and Economics*, 42, 13 – 19.

van Ours, J. C. and B. Vollaard (2016): "The Engine Immobiliser: A Non-starter for Car Thieves," *The Economic Journal*, 126, 1264–1291.

Vollaard, B. and J. C. van Ours (2011): "Does Regulation of Built-in Security Reduce Crime? Evidence from a Natural Experiment*," *The Economic Journal*, 121, 485–504.

A Additional Tables & Figures

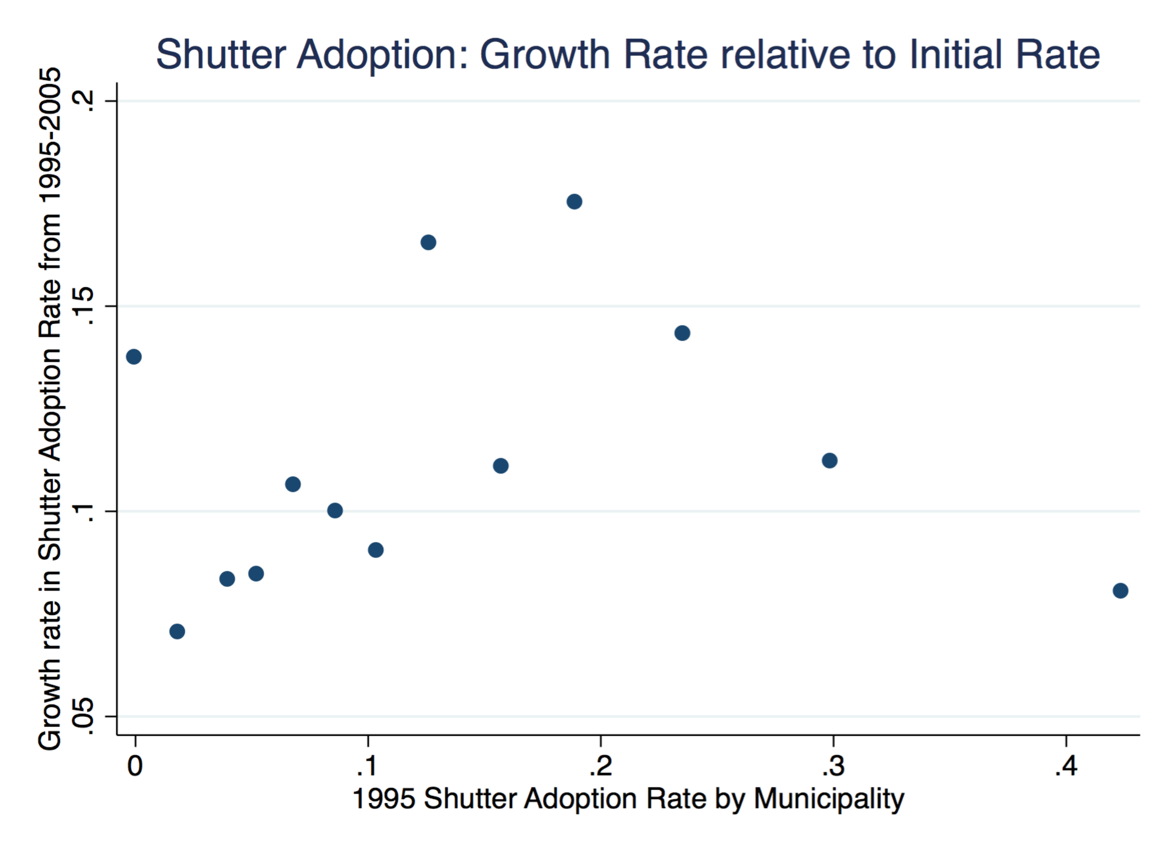


Figure 5

Table 7: Individual-Level Regressions of Precautionary Measure Use on Baselines Covariates and Municipality Location

	Shutters	Door Locks	Outdoor Lights	Burglar Alarms
Ethnic origin	-0.000	-0.042***	-0.070***	-0.008***
	(0.005)	(0.004)	(0.007)	(0.003)
Higher ed.	-0.049***	0.003	-0.027***	0.014***
	(0.005)	(0.004)	(0.008)	(0.005)
Income 10K€-20K€	-0.000	0.024***	0.008	-0.034***
	(0.007)	(0.008)	(0.009)	(0.007)
Income 20K€-30K€	0.013*	0.046***	0.050***	-0.044***
	(0.007)	(0.008)	(0.010)	(0.007)
Income 30K€-40K€	0.026***	0.066***	0.073***	-0.027***
	(0.007)	(0.008)	(0.011)	(0.007)
Income >40K€	0.025***	0.061***	0.090***	0.024***
	(0.007)	(0.008)	(0.011)	(0.007)
Income not reported	0.015	0.026**	0.054***	-0.001
	(0.009)	(0.011)	(0.012)	(0.008)
Benefit recipient	-0.006	-0.020**	-0.053***	-0.016**
	(0.007)	(0.008)	(0.008)	(0.007)
Wage earner	0.015**	-0.003	0.023***	0.024***
	(0.006)	(0.006)	(0.007)	(0.005)
Married	0.048***	0.041***	0.078***	0.023***
	(0.005)	(0.004)	(0.008)	(0.003)
Children (yes/no)	-0.012***	-0.000	-0.008**	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Happy neighborhood	0.015***	0.014***	0.044***	0.016***
	(0.004)	(0.004)	(0.006)	(0.004)
Police effectiveness	0.002	-0.003	-0.002	-0.003
	(0.003)	(0.003)	(0.004)	(0.003)
Feeling unsafe outside	0.011	0.007	-0.021**	0.025***
	(0.010)	(0.008)	(0.009)	(0.009)
Feeling unsafe at home	-0.023**	-0.002	-0.011	0.026***
	(0.009)	(0.009)	(0.011)	(0.009)
Victimized in last 5 yrs	0.001	-0.026**	-0.008	0.003
	(0.009)	(0.010)	(0.010)	(0.008)
Latitude	-0.207***	-0.007	-0.032**	-0.014***
	(0.008)	(0.005)	(0.013)	(0.004)
Longitude	0.065***	-0.011***	0.039***	-0.001
	(0.006)	(0.003)	(0.010)	(0.003)
Constant	10.646***	1.296***	2.299***	0.877***
	(0.435)	(0.233)	(0.653)	(0.195)
Age range dummies incl.	Yes	Yes	Yes	Yes
N	64,823	64,823	64,823	64,823
Adjusted R^2	0.093	0.014	0.059	0.015

Standard errors are clustered at the municipality level. All regressions also include individual controls, as described in section 3.

Table 8: Individual-Level Regressions of Precautionary Measure Use on Baselines Covariates and Municipality Fixed Effects

	Shutters	Door Locks	Outdoor Lights	Burglar Alarms
Age 25-34	-0.063***	0.002	-0.032***	-0.055***
	(0.006)	(0.006)	(0.008)	(0.005)
Age 35-44	-0.049***	0.013**	-0.009*	-0.014***
	(0.006)	(0.006)	(0.006)	(0.005)
Age 45-54	-0.060***	-0.000	-0.014**	-0.028***
	(0.006)	(0.007)	(0.006)	(0.005)
Age 45-64	-0.052***	0.004	0.005	-0.019***
	(0.006)	(0.007)	(0.007)	(0.006)
Age 65-74	-0.051***	0.002	0.008	0.008
	(0.009)	(0.009)	(0.009)	(0.008)
Age $\geq$ 75	-0.078***	-0.024**	-0.024*	0.048***
	(0.010)	(0.011)	(0.013)	(0.009)
Ethnic origin	0.010**	-0.044***	-0.048***	-0.007***
	(0.004)	(0.004)	(0.004)	(0.002)
Higher ed.	-0.036***	0.001	-0.012***	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)
2bn.hink_coef	-0.006	0.021**		-0.036***
	(0.007)	(0.008)	(0.008)	(0.007)
Income 20K€-30K€	0.009	0.043***	0.037***	-0.047***
	(0.007)	(0.008)	(0.008)	(0.007)
Income 30K€-40K€	0.021***	0.061***	0.056***	-0.031***
	(0.007)	(0.008)	(0.008)	(0.007)
Income >40K€	0.022***	0.055***	0.070***	0.019***
	(0.007)	(0.008)	(0.008)	(0.007)
Income not reported	0.011	0.024**	0.042***	-0.002
	(0.009)	(0.011)	(0.011)	(0.008)
Benefit recipient	-0.011	-0.018**	-0.050***	-0.015**
	(0.007)	(0.008)	(0.008)	(0.007)
Wage earner	0.010*	-0.002	0.017***	0.024***
	(0.006)	(0.006)	(0.006)	(0.005)
Married	0.042***	0.040***	0.058***	0.021***
	(0.004)	(0.004)	(0.004)	(0.003)
Children (yes/no)	-0.011***	-0.000	-0.009***	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)
Happy neighborhood	0.006	0.012***	0.023***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)
Police effectiveness	0.002	-0.001	0.002	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)
Feeling unsafe outside	0.019*	0.005	-0.009	0.025***
	(0.010)	(0.008)	(0.010)	(0.009)
Feeling unsafe at home	-0.022**	-0.003	-0.008	0.024***
	(0.009)	(0.009)	(0.011)	(0.009)
Victimized in last 5 yrs	-0.002	-0.024**	-0.008	0.004
	(0.009)	(0.010)	(0.009)	(0.008)
N	64,823	64,823	64,823	64,823
Adjusted R^2	0.124	0.023	0.099	0.021

Standard errors are clustered at the municipality level. All regressions also include individual controls, as described in section 3, and municipality-level fixed effects.

Table 9: Municipality-level regressions on baseline covariates

	(1) Shutters	(2) Burglary Alarm	(3) Outdoor light	(4) Door locks
Ethnic origin	0.326***	0.0558*	-0.136***	0.0636
	(0.0913)	(0.0306)	(0.0321)	(0.0476)
Higher Ed.	-0.467***	-0.0318	-0.0851**	0.0170
	(0.0950)	(0.0369)	(0.0412)	(0.0662)
Benefit recipient	0.874***	-0.104	0.00357	-0.196
	(0.309)	(0.114)	(0.124)	(0.226)
Wage earner	0.264	0.0457	0.0950	-0.0889
	(0.198)	(0.0860)	(0.0769)	(0.138)
Married	0.491***	-0.00117	0.247***	0.198***
	(0.127)	(0.0473)	(0.0435)	(0.0715)
Children (yes/no)	-0.134	0.0693	-0.162**	-0.114
	(0.137)	(0.0563)	(0.0678)	(0.110)
Happy neighborhood	0.118	0.154**	0.171**	0.0255
	(0.172)	(0.0627)	(0.0725)	(0.125)
Police effectiveness	0.0164	-0.0503	-0.0124	-0.170**
	(0.0960)	(0.0383)	(0.0400)	(0.0788)
Feeling unsafe outside	0.598	0.413**	0.0728	0.464**
	(0.396)	(0.163)	(0.156)	(0.206)
Feeling unsafe at home	1.059***	0.102	0.0622	0.0334
	(0.405)	(0.158)	(0.144)	(0.201)
Victimized in last 5 yrs	0.158	-0.000176	0.272*	0.411
	(0.196)	(0.0849)	(0.143)	(0.290)
Age 25-44	-0.444	0.0180	-0.170	-0.155
	(0.526)	(0.188)	(0.227)	(0.312)
Age 45-64	0.760*	0.153	0.432***	-0.235
	(0.420)	(0.160)	(0.165)	(0.266)
Age $\geq$65	0.190	0.110	0.0380	-0.448*
	(0.455)	(0.178)	(0.172)	(0.229)
Income <$10K	-0.193	0.0575	-0.373***	-0.210
	(0.333)	(0.114)	(0.141)	(0.247)
Income $10-20K	-0.490*	0.0420	-0.166	0.132
	(0.287)	(0.114)	(0.116)	(0.213)
Income $20-30K	-0.210	0.0334	-0.243*	-0.111
	(0.265)	(0.0997)	(0.136)	(0.239)
Income $30-40K	0.0384	0.182*	-0.104	0.133
	(0.264)	(0.0975)	(0.130)	(0.234)
Income >$40K	-0.160	0.250**	-0.141	0.238
	(0.270)	(0.105)	(0.120)	(0.212)
Constant	-0.993*	-0.302	0.277	0.135
	(0.525)	(0.215)	(0.232)	(0.493)
Obs.	443	443	443	443
Adj. R^2	0.212	0.176	0.477	0.218

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 10: Individual-Level Regressions of Shutter Use on Baselines Covariates and Spatially Lagged Shutter Prevalence (Probit)

	Inverse Distance	Inverse Distance (South Only)	Neighbors	Neighbors (North Only)
Shutters (Spatial Lag)	8.450***	6.882***	3.235***	2.572***
	(0.283)	(0.280)	(0.084)	(0.183)
Ethnic origin	0.040**	0.023	0.043**	0.043**
	(0.020)	(0.018)	(0.020)	(0.017)
Higher ed.	-0.196***	-0.202***	-0.183***	-0.194***
	(0.020)	(0.020)	(0.019)	(0.019)
Income 10K€-20K€	-0.022	-0.013	-0.029	-0.030
	(0.033)	(0.034)	(0.033)	(0.033)
Income 20K€-30K€	0.036	0.046	0.033	0.028
	(0.032)	(0.033)	(0.032)	(0.032)
Income 30K€-40K€	0.093***	0.100***	0.088***	0.080**
	(0.033)	(0.033)	(0.033)	(0.034)
Income >40K€	0.107***	0.105***	0.101***	0.089**
	(0.033)	(0.034)	(0.033)	(0.035)
Income not reported	0.057	0.062	0.047	0.048
	(0.043)	(0.044)	(0.043)	(0.042)
Benefit recipient	-0.025	-0.019	-0.029	-0.017
	(0.032)	(0.032)	(0.032)	(0.032)
Wage earner	0.052**	0.050**	0.044*	0.051**
	(0.025)	(0.025)	(0.025)	(0.024)
Married	0.196***	0.204***	0.196***	0.204***
	(0.017)	(0.017)	(0.017)	(0.017)
Children (yes/no)	-0.046***	-0.046***	-0.043***	-0.043***
	(0.014)	(0.014)	(0.014)	(0.014)
Happy neighborhood	0.051***	0.059***	0.048***	0.046**
	(0.018)	(0.018)	(0.018)	(0.019)
Police effectiveness	0.009	0.015	0.010	0.003
	(0.013)	(0.013)	(0.013)	(0.013)
Feeling unsafe outside	0.052	0.047	0.066	0.083**
	(0.042)	(0.041)	(0.041)	(0.041)
Feeling unsafe at home	-0.108***	-0.102***	-0.092**	-0.094**
	(0.040)	(0.040)	(0.040)	(0.038)
Victimized in last 5 yrs	0.001	0.001	0.002	0.008
	(0.038)	(0.038)	(0.038)	(0.037)
Other precautions	0.870***	0.883***	0.880***	0.841***
	(0.059)	(0.057)	(0.056)	(0.061)
Constant	-3.473***	-2.745***	-2.474***	-2.297***
	(0.121)	(0.117)	(0.117)	(0.144)
Age range dummies incl.	Yes	Yes	Yes	Yes
N	64,823	64,823	64,823	64,823
Log Likelihood	-2.77e+04	-2.78e+04	-2.75e+04	-2.84e+04

Standard errors are clustered at the municipality level. All regressions also include individual controls, as described in section 3.

Table 11: Spatial autocorrelation of baseline covariates

	Global Autocorrelation		*North-South Contagion*	
	Moran's I	z-Score	Moran's I	z-Score
Ethnic origin	0.053***	15.228	0.056***	8.952
Higher Ed.	0.060***	17.243	0.100***	15.694
Benefit recipient	0.040***	11.649	0.047***	7.618
Wage earner	0.030***	8.908	0.019***	3.260
Married	0.017***	5.285	0.019***	3.311
Children (yes/no)	0.017***	5.317	0.016**	2.802
Happy neighborhood	0.010***	3.425	-0.006	-0.573
Police effectiveness	0.067***	19.326	0.151***	23.469
Feeling unsafe outside	0.028***	8.513	0.049***	7.897
Feeling unsafe at home	0.030***	8.873	0.040***	6.498
Victimized in last 5 yrs	-0.004	0.324	-0.006	-0.604
Age 15-24	0.036***	10.700	0.051***	8.256
Age 25-44	0.039***	11.412	0.031***	5.073
Age 45-64	0.036***	10.678	0.036***	5.904
Age $\geq$65	0.041***	12.089	0.044***	7.140
Income $\$< 10K$	0.002	1.088	-0.004	-0.259
Income \$10-20K	0.060***	17.407	0.117***	18.313
Income \$20-30K	0.056***	16.140	0.132***	20.607
Income \$30-40K	0.003*	1.343	0.011*	1.965
Income \$> 40K	0.099***	28.205	0.222***	34.432

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 12: Growth Rate in Shutter Adoption on Initial Municipality Characteristics

	(1)	(2)
Shutters rate 95 squared	-0.814***	-0.821***
	(0.107)	(0.107)
Shutters rate 95	0.0336	0.0387
	(0.0726)	(0.0727)
Change in income		-0.0307
		(0.0269)
Constant	0.109***	0.111***
	(0.00763)	(0.00774)
N	423	423
R^2	0.354	0.356