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Estimating the Impact of Forced Sales on House Prices

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Abstract

We study the price effects of forced sales on the Dutch housing market. A forced sale may result in a lower transaction price because of e.g. suboptimal incentives for revenue maximization. The lower transaction price may also spill over to regular (unforced) nearby transactions. We aim to measure both the forced sale discount and the spillover effect. We employ an unusual rich dataset for house transactions in the Netherlands between 2007 and 2013. To identify the effects of forced sales we control for very local neighborhood trends and detailed house characteristics. We find that a forced sale results in a price discount of about five percent. Each nearby forced sale reduces the transaction price by about 0.4 percent.

JEL Classification Numbers: G21, R20 and R31.
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1 Introduction

The 2007/2008 financial crisis led to a severe housing slump in many countries. As house prices declined, the number of forced sales soared in developed economies such as the United States and the Netherlands. An

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unprecedented number of households were unable to repay their mortgage and had to sell their houses. For instance, observed forced house sales in the Netherlands more than tripled in recent years and the number of persons with mortgage arrears increased from about 30,000 in 2008 to 100,000 in 2014.[1]

It is widely believed that forced sales entail negative externalities. Policy makers and home owners worry for instance that nearby forced sales reduce local house prices or, through property neglect, lead to a declining attractiveness of neighborhoods. A growing literature confirms this belief, but only for US housing markets. Thus far, it is unclear whether these findings can be extrapolated to other countries. Our paper is the first to study the impact of forced sales in the Netherlands. Similar to the US, the housing market in the Netherlands first experienced a prolonged boom until 2008 and subsequently a severe bust in which prices dropped on average with 20 percent. Unlike the US, however, the Netherlands has a more generous social safety net and a widespread system of mortgage insurance, which enables us to assess whether foreclosures also have effects on house prices in a different institutional context.

In this paper we estimate price effects of forced sales. A forced sale may have two distinct price effects. First, when a house is foreclosed[2] (i.e. sold at the insistence of the bank), the transaction price of that house may be lower than if the sale would have been unforced. We refer to this as the forced sale or the foreclosure discount. Foreclosed properties may sell at a discount because banks possibly wish to sell quickly. Consistent with this hypothesis, Levitt & Syverson (2008) find that houses that are 9.5 days longer on the market sell for 3.7 percent more. Another possible reason for the foreclosure discount is that owners' incentives for home maintenance may be reduced once in a foreclosure procedure. Several studies for US housing markets estimate a foreclosure discount between 22 percent and even 50 percent, depending on the region and time period.[3]

The second potential effect of forced sales is the indirect negative impact on the transaction price of nearby regular sales. This is called the contagion or spillover effect. A simple potential channel of the spillover effect is that a forced sale increases supply on local housing markets. The resulting shift of the supply function yields a reduced market price. The

[1] *Source:* BKR (2014).

[2] We use the terms "forced sale" and "foreclosure" interchangeably. See section 3 for a description of the foreclosure procedure in the Netherlands.

[3] See for instance Pennington-Cross (2006), Shilling, Benjamin & Sirmans (1990) and Sumell (2009).

spillover effect may also arise from the use of buyers and sellers of historic transaction prices as reference prices in negotiations. Non-financial externalities could play a role as well. If, for instance, the foreclosed house is poorly maintained, the diminished visual appearance of a house may make it less attractive to live in its direct vicinity. The typical estimate of the spillover effect is that each nearby foreclosure lowers transaction prices with about one percent.[4]

Alternatively, one may argue that arbitrage opportunities should limit the magnitude or even completely undo the price effects of forced sales. If foreclosed houses sell sufficiently below their true market value, traders could buy the foreclosed property and sell it quickly on the regular market. Thus, the impact of a foreclosure on house prices is ultimately an empirical matter.

Identification of the direct and indirect price effects of forced sales is complicated because the "treatment" of a forced sale is not random across transactions. This yields three methodological challenges. First, it is likely that the event of a forced sale is correlated with other, potentially non-observed (to the econometrician) variables, which may give rise to omitted variables bias. A second problem is that the relation between forced sales and house prices may be spurious. If, for instance, an employment shock hits a neighborhood (e.g. a closure of a large plant), redundant workers may start to miss their interest payments while demand for local housing drops. The third issue is reverse causality. Our data is such that we only observe a forced sale for households with mortgage insurance and who were left with a residual mortgage debt after the forced sale of their house. As residual mortgage debt is more likely in times of declining house prices, decreasing house prices may lead to more observed forced sales.

Our identification strategy rests on three pillars. First, we exploit an unusually rich dataset with detailed information on house characteristics. Our data contains information on about 750,000 Dutch transactions between 2007 and 2013.[5] Similar to existing studies, we observe many standard characteristics, such as the size, the number of rooms or the year of construction. Additionally, we have data that is rare in the literature – such as the quality of maintenance of the interior and the exterior of the house, whether the house is located on a busy road or whether the garden

[4]Examples are Campbell, Giglio & Pathak (2011) and Harding, Rosenblatt & Yao (2009).

[5]This constitutes about 76 percent of all transactions on the Dutch housing market.

faces south. Second, to correct for the possibility of region specific time trends, we include dummies for about 3,000 regions for each year. Third, based on the approach of Campbell et al. (2011), we control for very local neighborhood effects and reverse causality. In particular, in our hedonic regression we include the number of forced sales in a small radius of 100 meters and in a wider radius 250 meters to control for local effects. We address reverse causality by inclusion of the number of forced sales one year before and one year after a regular sale.

We find that forced sales have a statistically and economically significant direct effect. On average, the foreclosure discount is about five percent. We obtain very similar results with a repeat sales regression. The estimates for the spillover effect range between 0.3 and 0.5 percent. The statistical significance varies with the approach and specification. Overall, as most regular sales have at most one forced sale in the vicinity, the consequences of nearby forced sales on transaction prices seem modest.

In the next section we discuss the related literature. In section 4 we explain our identification strategy in more detail. Then, we describe our data and offer a few descriptive statistics in section 5. The main results are presented in section 6. Our concluding remarks can be found in section 7.

2 Related Literature

The interest of economists in the effects of forced sales grew after the subprime crisis took off in 2007. By now, there is a sizable literature that focuses on this topic. Table 10 in the appendix summarizes the empirical literature on foreclosures. Remarkably, the literature is dominated by US housing market studies and we are not aware of reliable estimates for European countries or the Netherlands in particular.

To estimate the foreclosure discount (or the direct effect), most studies adopt a hedonic regression approach. These papers usually explain transaction prices with house characteristics, neighborhood dummies and a dummy that indicates whether the house was foreclosed. Identification of the foreclosure discount is particularly problematic with a hedonic regression, because a forced sale may be correlated with unobservable factors, such as poor property maintenance. A few earlier studies do not satisfactorily address this omitted variables bias and obtain high estimates of the foreclosure discount. Examples are Shilling et al. (1990) (discount 24 percent) and Sumell (2009) (discount 50 percent). In a more comprehensive study, Campbell et al. (2011) use information on the mechanism and the cause of the forced sale to disaggregate the forced sale discount. They find the strongest effects for foreclosure auctions (27 percent), while the discount is much lower when the forced sale is related to death or bankruptcy (3 to 7 percent) of the owner.

The hedonic regression has also been applied to estimate the contagion effect (or the indirect effect). The typical regression features a vector of house characteristics and a variable that indicates the number of forced sales within a certain distance of the regular sale. Based on this set-up, Immergluck & Smith (2006) and Schuetz, Been & Ellen (2008) both find evidence for a contagion effect. However, it is possible that such studies fail to identify the causal effect of nearby forced sales, because local economic shocks may simultaneously cause lower house prices and forced sales. Moreover, local house prices declines may lead to more foreclosures. If, for instance, home-owners can "walk away" from their mortgage, this results in a reverse causality problem. Campbell et al. (2011) suggest to address these difficulties by augmenting the hedonic regression with a count of the forced sales in a wider area and a count of the forced sales *after* the regular sale. Using this approach they still find a contagion effect of about 1 percent per foreclosure within a radius of 0.05 miles.

Various other studies use a repeat sales strategy to estimate the contagion effect. A notable difference between these papers and our study is that we observe house characteristics at both transaction dates, whereas other papers do not observe these characteristics. For instance, in an otherwise careful repeat sales study, Fisher, Lambie-Hanson & Willen (2014) assume that house characteristics remain constant across transactions of the same object. For condominium transactions with the same address and the same association, they find a strong contagion discount of 2.5 percent. Harding et al. (2009) use a repeat-sales model to estimate the contagion effect in 7 large US regions. They find a 1 percent price discount per foreclosure within a 300 feet radius of a regular sale. This effect diminishes quickly when the size of the ring is increased. Gerardi, Rosenblatt, Willen & Yao (2012) find very similar results.

3 Institutional Setting

We provide a detailed description of the Dutch national mortgage insurance fund in this section as the forced sales in our dataset all stem from this institution.

By the end of 2012 the Dutch housing stock consists of approximately 7.3 million dwellings, of which 56 percent is owner-occupied. Since the late eighties, the main objective of Dutch housing policy is to increase home ownership. One of the government measures to achieve that goal is the establishment of the National Mortage Guarantee (NHG, or Nationale Hypotheek Garantie). NHG aims to promote home ownership among the lower and middle income classes by insuring both borrowers and lenders against the risk of residual mortgage debt. The share of outstanding mortgage debt in the Netherlands backed by an NHG-guarantee is currently about 25 percent. And in the lower segment of properties below 265,000 euro, the penetration of NHG is 82 percent in 2013.[6]

For a one-off charge of the principal amount of the mortgage loan[7], borrowers can take out a mortgage with a NHG-guarantee. The mortgage should not exceed an upper limit, which is currently set at 265,000 euro.[8] In addition there are restrictions on the borrower's debt-to-income ratio. The mortgage lender is responsible for checking that these conditions are met. Mortgage lenders offer a discount on the interest rate, up to an estimated 0.6 percent, because of the cheap hedge for credit risk on NHG-backed loans and the zero regulatory capital requirements due to the fact that the Dutch state ultimately backs the NHG-scheme.

In case a borrower took out an NHG-guaranteed mortgage loan, the NHG will pay out any remaining shortfall to the lender in the event of a forced sale (either via an auction or a sale on the market). However, both the borrower and the lender have to fulfill a number of requirements before the NHG indemnifies the residual debt. The main requirements are, first, that the forced sale must be caused by disability, divorce, death or involuntary and non-preventable unemployment of the borrower. Second, the borrower needs to ensure that the property is well-maintained. This limits the scope for negative physical externalities to the neighborhood. Third, the borrower should do everything possible to limit the residual debt.

The lender should as well meet a number of criteria before the NHG turns to compensation of the residual debt. For instance, the NHG will only compensate the full claim if the loan complies with all the conditions of an NHG guaranteed mortgage. Secondly, the NHG covers the losses mortgage lenders incur on a loan. The coverage, however, amortizes ir-

[6] *Source:* NHG.

[7] The fee was 0.7 percent in 2012, 0.85 percent in 2013 and 1 percent of the mortgage in 2014.

[8] This number includes additional expenses (e.g. notary costs) of 6 percent, meaning that the price limit for the property is in fact 250,000 euro. In July 2009 the NHG-ceiling was temporarily increased to 350,000 euro, while the ceiling was gradually decreased back to 265,000 euro in July 2014 (320,000 in July 2012; 290,000 in July 2013).

respective of the loan type on a monthly, 30-year annuity basis. Thirdly, since 2012, the NHG requires a selling price of at least 95 percent of the assessed market value of the property. If one or more conditions have not been met, the NHG may decide to limit or refrain from compensation.

Note that the NHG only compensates the lender's shortfall when the forced sale resulted in a residual debt. During a period of declining house prices, it is therefore likely that the number of forced sales in our NHG dataset increases. On the surface, it seems that declining house prices cause an increase in the number of NHG-forced sales. In our estimation strategy below, we describe how we cope with this problem of reverse causality.

4 Estimation Strategy

The estimation of a causal relation between forced sales and house prices is an econometric challenge, because forced sales are not random across transactions. The incidence of forced sales may be related to variables that partly determine the transaction price. A foreclosed home-owner, for instance, is likely to lack financial resources (and possibly also the right incentives) for proper maintenance. Similarly, a local demand shock – such as the closure of a large firm – may simultaneously yield lower house prices and more foreclosures. This is because a bankruptcy of a large firm may decrease long term regional employment, which also depresses regional housing demand and incomes.

4.1 Identification of the foreclosure discount

We address the omitted variables bias by exploiting a rich dataset that includes detailed information on properties, both on objectively measurable variables, such as the number of square meters, but also many subjective indicators. We observe, for instance, the (stated) level of maintenance of the interior or the proximity to a park or a busy road. We also include narrowly defined region–year dummies.

As is common in the literature, we estimate a hedonic regression of the form[9]:

$$ln(p_{ilt}) = \alpha_{lt} + \beta' \mathbf{X}_{it} + \gamma F_{it} + \epsilon_{ilt}, \tag{1}$$

[9] Another common approach is the repeat sales framework. We present the results from a repeat sales regression as a robustness check in section 6.1.

where $ln(p_{ilt})$ is the log of the real price of transaction i in region l and year t. Local housing trends are captured with the dummy α_{lt}, which indicates a four-digit ZIP code area for each year.[10] The vector $\mathbf{X}_{it}$ contains house and sale characteristics.[11] F_{it} is a dummy variable equal to 1 if a property is a forced sale and 0 otherwise. The coefficient γ estimates the foreclosure discount.

4.2 Identification of the contagion effect

We also rely on a hedonic regression for the measurement of the contagion (or spillover) effect of forced sales on the price at regular transactions. The equation that we estimate is:

$$ln(p_{ilt}) = \alpha_{lt} + \beta'\mathbf{X}_{it} + \gamma_1 NF_{it}^{\mathrm{C,B}} + \gamma_2 NF_{it}^{\mathrm{C,A}} + \gamma_3 NF_{it}^{\mathrm{F,B}} + \gamma_4 NF_{it}^{\mathrm{F,A}} + \epsilon_{ilt}. \quad (2)$$

Here, the variable $NF^{\mathrm{C,B}}$ indicates the number of close forced sales within a radius of 100 meters, 1 year before the regular sale. $NF^{\mathrm{C,A}}$ corresponds to the number of close forced sales 1 year after 100 days after the regular sale.[12] $NF^{\mathrm{F,B}}$ represents the number of far forced sales within a radius of 250 meters before the regular sale. Finally, $NF^{\mathrm{F,A}}$ is the number of far forced sales, 1 year after 100 days after the regular sale.

Following Campbell *et al.* (2011), equation 2 adapts the hedonic regression with different counts of the number nearby forced sales. The idea behind including $NF^{\mathrm{F,B}}$ is that local neighborhood shocks affect house prices and are correlated with the number of forced sales within a broad local area. Additionally, we add counts of the number of forced sales after the regular sale to control for reverse causality. Our estimate of the spillover effect is given by the difference between γ_1 and γ_2.

[10] The four-digit ZIP code level gives a very detailed partitioning of the country, with about 4,000 different four-digit ZIP codes in the Netherlands. On average, we observe 31 transactions per four-digit ZIP code area per year.

[11] We describe our data in section 5.

[12] We consider forced sales that occur after a period of 100 days after the regular sale, because forced sales that take place shortly after the regular sales may have competed directly on the local housing market.

5 Data

We construct a new dataset from three different sources. The core of our data consists of data from the "Nederlandse Vereniging voor Makelaars" (NVM), which is the largest association of brokers and real estate experts in the Netherlands. The dataset from NVM includes detailed information on 749,716 NVM-mediated house transactions between 2007 and 2013.

Table 1: Share of NVM brokers on Dutch housing market

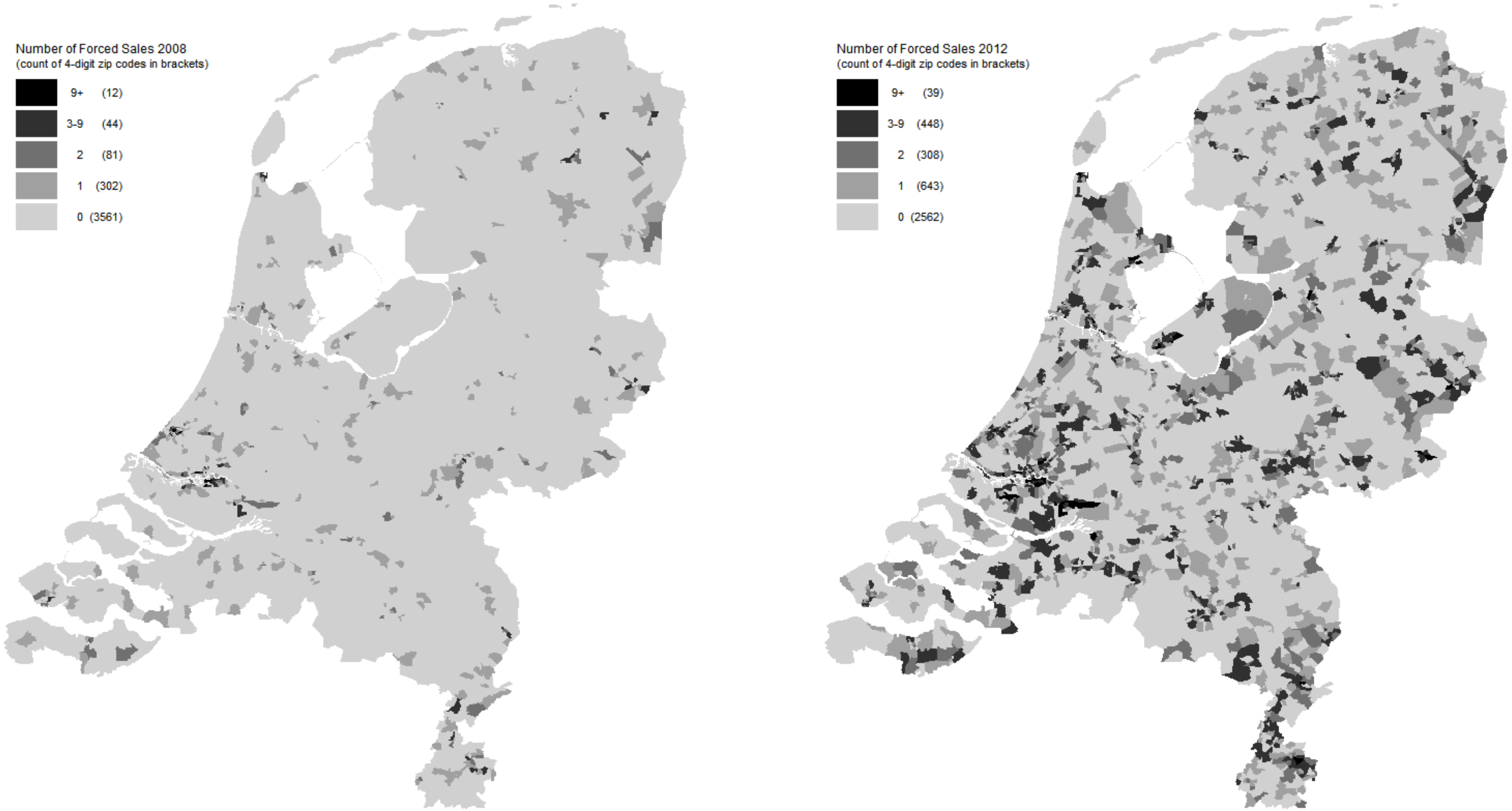
	Number of Sales		**Market share**	**Average price**	
	Netherlands	*NVM*	*NVM*	*Netherlands*	*NVM*
2007	202 401	149 318	0.74	248 325	263 295
2008	182 392	127 661	0.70	254 918	263 898
2009	127 532	98 182	0.77	238 259	244 110
2010	126 127	99 710	0.79	239 530	250 980
2011	120 739	90 987	0.75	240 059	247 834
2012	117 261	93 789	0.80	226 661	228 211
2013	110 094	90 068	0.82	213 353	222 026

Source: Statistics Netherlands and NVM.

As table 1 shows, the vast majority of sellers on the Dutch housing market hires an NVM realtor. The mean price of NVM-mediated transactions is between 2 and 6 percent higher than the average selling price in the Netherlands.

The NVM dataset contains information on more than 30 house transaction characteristics. Naturally, this includes traditional data on the transaction price, the address or the year of construction, but also less common variables such as the interior and exterior state of maintenance, the proximity to a park or the orientation of the garden. Appendix B provides an overview of the house characteristics that we include in all of our hedonic regressions.

Figure 1: Distribution of Forced Sales in the Netherlands



In addition to data from NVM, we obtained data on 12,476 forced sales in the period 2007-October 2013 from the NHG. For privacy reasons, the NHG did not provide us data on the exact address of forced sales. We do know, however, the transaction price, the transaction date and the six-digit ZIP code of each NHG forced sale. Based on these variables, we were able to link 6,901 forced sales to a transaction in the NVM dataset.[13] Therefore, for a subset of all NHG forced sales, we could retrieve detailed property information.

The third source for our dataset is Statistics Netherlands. We obtained data on distances between about 430,000 six-digit ZIP code areas to calculate the number of nearby forced sales for each regular transaction within a relatively small radius ($\leq$ 100 meters or $\leq$ 250 meters) and within a certain time frame (one year before the regular transaction and one year after a hundred days after the regular transaction).

Table 2 shows averages for a selection of house characteristics for four cross sections: *i*) all matched forced sales, *ii*) all regular sales located in a ZIP code area with at least one foreclosure within the same year, *iii*) regular sales below the NHG price ceiling, and *iv*) all observed regular sales. Comparing the first column with the fourth column, we see that the transaction price of forced sales in our dataset is over 100,000 euro lower than the selling price associated with regular sales. This price differential can be partially attributed to the fact that the foreclosures in our dataset are all below the NHG price ceiling, as the price differential more than halves when comparing forced sales with regular sales below the NHG-ceiling. The price differential is smallest between foreclosures and regular sales in the same ZIP code area.

In Table 3 we provide information on the distribution of the number of nearby forced sales. Table 3(a) shows that about 89 percent of the regular sales in our dataset have no nearby forced sales within a radius of 250 meters in the year before or after the transaction. This number increases to 96 percent when we decrease the radius to 100 meters. About eight percent of the regular sales have exactly one forced sale in their neighborhood.

[13] The transaction prices reported by NHG and NVM often did not exactly match. We therefore allowed NHG prices to be in an interval -7 percent and +7 percent of the NVM transaction price. Of the 12,476 forced sales, about one fifth is auctioned. We could not match any of the auctioned properties to the NVM data because NVM realtors do not intermediate in foreclosure auctions. We therefore linked 6,901/9,652$\approx$70% of the NHG observations to the NVM data. As a robustness check, available upon request, we also required an exact match of the NHG and NVM prices. This resulted in 3,277 matched observations, and no noteworthy changes of the regression results.

Table 2: House characteristics: four cross sections

	Forced	Regular *near forced sales*	Regular *lower segment*	Regular *all*
Real sales price	161987	169292	201495	267761
Square meters (m^2)	102	96	103	117
Detached	0.03	0.02	0.07	0.13
Semi-detached	0.10	0.06	0.12	0.14
Single-family	0.68	0.49	0.56	0.53
Maintenance inside				
<Good	0.15	0.13	0.15	0.14
Good	0.75	0.74	0.73	0.72
Good/Excellent	0.02	0.03	0.02	0.03
Excellent	0.07	0.11	0.09	0.12
Maintenance outside				
<Good	0.14	0.09	0.10	0.09
Good	0.79	0.80	0.80	0.79
Good/Excellent	0.02	0.02	0.02	0.02
Excellent	0.05	0.09	0.07	0.10
Observations	6109	3657	573841	743607

Source: NHG and NVM. "Forced" are all forced sales that we could link to the house characteristics data of NVM. The "Regular near forced sales" are regular sales that occur in the same year and in the same ZIP-code area as a forced sale. "Regular lower segment" describes all regular sales with transaction prices below the NHG-threshold. Finally, "Regular all" gives an overview of characteristics of all regular sales in our data.

Two nearby forced sales occur far less frequently (1.5%) and three or four nearby forced sales are rarer still.

To illustrate the effect of the increase in the number of forced sales we show the distribution of nearby forced sales in 2012 in Table 3(b). The distribution is still skewed and, in line with the picture that emerges from Figure 1, we observe a substantial increase in the number of regular sales with a positive number of nearby forced sales.

Table 3: Distribution of number of nearby foreclosures

(a) Full sample (2007-2013)

	NF pre far	NF post far	NF pre close	NF post close
0 (%)	89.33	89.33	96.42	96.43
1 (%)	8.05	8.10	3.12	3.12
2 (%)	1.55	1.56	0.34	0.34
3 (%)	0.49	0.46	0.08	0.07
≥ 4 (%)	0.58	0.54	0.04	0.04
Observations	749716	749716	749716	749716

(b) Restricted sample (2012)

	NF pre far	NF post far	NF pre close	NF post close
0 (%)	82.64	80.29	94.28	93.69
1 (%)	13.05	14.84	5.05	5.56
2 (%)	2.68	3.29	0.52	0.62
3 (%)	0.91	0.97	0.11	0.10
≥ 4 (%)	0.73	0.62	0.05	0.04
Observations	93789	93789	93789	93789

6 Main results

Table 4 presents the estimates of the hedonic regressions. For practical considerations, we only show the estimates of the foreclosure and contagion discount. The estimated coefficients for the house characteristics all have the expected signs and the adjusted R^2 is relatively high at 0.86. We show the full regression results (excluding the ZIP code-year dummies) for the hedonic regression in Appendix C.

Model I shows that a foreclosed home, on the regular market, is associated with a lower price of about 5 percent. This estimate of the foreclosure discount is economically significant, but much lower than previous estimates for US housing markets.

As a first attempt to estimate the spillover effect of forced sales, model II includes only the number of forced sales within a radius of 100 meters.

Table 4: Hedonic regressions

	I	II	III
	b/se	b/se	b/se
Foreclosed	-0.054***		
	(0.002)		
NF pre close		-0.029***	-0.014***
		(0.002)	(0.002)
NF post close			-0.011***
			(0.002)
NF pre far			-0.012***
			(0.002)
NF post far			-0.011***
			(0.002)
N	749168	743061	743061
Adjusted R^2	0.855	0.854	0.855
Contagion discount (%)			-0.31
p-value			0.0709

Note: These regressions have the logarithm of the real transaction price as the dependent variable. As regressors we include ZIP code (4 digit)-year dummies, monthly dummies and house characteristics. The numbers between round brackets are clustered standard errors at the level of the 4 digit ZIP code. Legend: *: p<.05, **: p<.01 and ***: p<.001. The contagion discount gives the difference between the coefficients for the number of nearby (<100m) foreclosures before and after each regular sale. The p-value in the bottom line is the probability value for the Wald test of this difference (or the contagion discount).

Note that the number of observations decreases from model I to model II, because we only estimate the spillover effect on regular sales. The estimated coefficient is -0.029, which suggests that each additional nearby forced sale has a strong impact on the transaction price of regular sales of about 3 percent.

However, the more sophisticated estimation strategy in Model III leads to a different conclusion. The estimated coefficients for the number of nearby forced sales before and after the regular sale have similar values, which suggests that nearby forced sales mainly reflect local housing market trends. The difference between the coefficients γ_1 and γ_2 in equation (2) is small (0.0031, or 0,3 percent). For a home with a value of 170,000 euro (which is roughly the value of regular sales in the vicinity of forced sales), this corresponds to an effect of about 510 euro per nearby forced sale. The p-value of the Wald test of equality is 0.0575, which is above the conventional level of statistical significance.

In the above regressions, we estimated the spillover effect of foreclosures on all regular sales, including properties with prices above the threshold of NHG. As we only have foreclosure data for properties below the NHG-threshold, our baseline set-up essentially tries to find a spillover effect of low-priced forced sales on (possibly) much more expensive properties. This seems the correct approach if the mechanism behind the spillover effect lies in non-financial externalities such as poor maintenance. However, if the main channel of the spillover effect is a financial externality (such as an increase in local housing supply), we would expect that the spillover effect is limited to comparable properties. To account for this possibility, we also estimate our hedonic regressions for the subsample of all regular sales below the NHG-threshold. Table 5 presents the regression outcomes.

We find that the estimated coefficients of Model I and II are similar to our baseline estimates in Table 4. The outcome of Model III, however, is different from our baseline estimates. We find a statistically significant contagion discount of about 0.4 percent (p-value is 0.0185). This result shows that nearby foreclosures have a small negative impact on the selling price of houses below the NHG-threshold. The fact that the contagion discount is larger and more significant for this subsample suggests that the contagion discount is caused by a supply or price discovery effect.

So far we assumed a constant (*i.e.* time-independent) foreclosure discount. The NHG notes that they impose a stricter requirement on the selling price of foreclosed properties. In particular, since 2012 the selling price in a foreclosure procedure should be at least 95 percent of the assessed market value. We do not know what the policy of NHG was before 2012, but if NHG indeed applied more stringent conditions, we expect discounts of foreclosed properties to decrease in the last two years of our sample. To examine this possibility, we allow for a different foreclosure discount for 2012 and 2013 in our hedonic specification of Model I in Table 4.

See Table 6 for the estimates of the time-varying foreclosure discounts. We find an average foreclosure discount of 5.5 percent ($1 - \exp -0.057$) in the period 2007-2011. In line with our expectations, the foreclosure discount drops to 5.1 percent ($1 - \exp -0.52$) in the years 2012 and 2013. The

Table 5: Hedonic regression: below NHG-threshold

	I	II	III
	b/se	b/se	b/se
Foreclosed	-0.059***		
	(0.002)		
NF pre close		-0.030***	-0.018***
		(0.002)	(0.002)
NF post close			-0.014***
			(0.002)
NF pre far			-0.009***
			(0.001)
NF post far			-0.009***
			(0.001)
N	579608	573501	573501
Adjusted R^2	0.764	0.763	0.763
Contagion discount (%)			-0.38
p-value			0.0185

Note: Dependent variable: the logarithm of the real transaction price. Clustered standard errors at the level of the 4 digit ZIP code. Legend: *: p<.05, **: p<.01 and ***: p<.001. The contagion discount gives the difference between the coefficients for the number of nearby (<100m) foreclosures before and after each regular sale. The p-value in the bottom line is the probability value for the Wald test of this difference (or the contagion discount).

two coefficients are, however, not statistically different from each other.[14]

6.1 Robustness

In this section we present the results from two additional regression models. First, we consider a different specification of the hedonic model.

In our baseline setup, we included a simple count of the number of forced sales. This specification implicitly assumes that the marginal effect of nearby forced sales is constant. In Table 7, we check how our results change if we include instead dummy variables for the number of nearby foreclosures. Specifically, we include dummies for exactly one foreclosure and dummies for two or more foreclosures, within a radius of 100 or 250

[14]The p-value of a Wald test of equal coefficients is 0.219.

Table 6: Time-varying foreclosure discount

	I b/se
Foreclosed 2007-2011	-0.057***
	(0.003)
Foreclosed 2012-2013	-0.052***
	(0.003)
N	749168
Adjusted R^2	0.855

Note: Estimates are from a hedonic regression of the log real transaction price on house characteristics and ZIP-code-year dummies. The standard errors are clustered at the level of the 4 digit ZIP code. Legend: *: p<.05, **: p<.01 and ***: p<.001. The table only presents estimates coefficients for the foreclosure dummy.

meters, in the year before and the year after the regular sale. In model I we estimate this piece-wise linear specification for the full sample, whereas in model II we estimate the model only for properties sold below the NHG-threshold.

In model I we find a contagion discount of 0.49 percent (p-value 0.0228) for exactly one nearby forced sale. The contagion discount of two or more nearby forced sales is about the same, but not significant. Model II shows that the contagion discount of exactly one nearby forced sale is larger in the sample with properties below the NHG-threshold. This confirms our previous finding that nearby forced sales have a stronger effect on the price of more comparable houses.

To the extent that the dataset is sufficiently rich, the omitted variables bias will be mitigated, and we can be reasonably confident that equation (1) yields a good estimate of the direct effect of forced sales. However, we should be cautious as the hedonic regression could still miss important determinants of the property value. For instance, forced sales may predominantly occur in "bad" neighborhoods, which may erroneously result in a high estimate of the forced sale discount.

We address this issue by employing a repeat-sales regression framework. In this framework, we try to explain the change in the transaction price of the *same* object at *different* transaction dates. By design, this set-up

Table 7: Piece-wise linear hedonic regression

	Full sample b/se	Lower segment b/se
NF pre close = 1	-0.015***	-0.019***
	(0.003)	(0.003)
NF post close = 1	-0.010***	-0.013***
	(0.002)	(0.002)
NF pre close >1	-0.035***	-0.042***
	(0.006)	(0.006)
NF post close >1	-0.031***	-0.038***
	(0.006)	(0.005)
NF pre far = 1	-0.020***	-0.015***
	(0.001)	(0.001)
NF post far = 1	-0.020***	-0.016***
	(0.001)	(0.001)
NF pre far >1	-0.038***	-0.032***
	(0.003)	(0.003)
NF post far >1	-0.031***	-0.028***
	(0.003)	(0.003)
N	743061	573501
Adjusted R^2	0.855	0.763
Contagion discount NF = 1 (%)	-0.49	-0.65
p-value	0.0228	0.0011
Contagion discount NF >1 (%)	-0.44	-0.33
p-value	0.4539	0.5391

Note: Dependent variable: the logarithm of the real transaction price. Clustered standard errors at the level of the 4 digit ZIP code. Legend: *: p<.05, **: p<.01 and ***: p<.001. The contagion discount gives the difference between the coefficients for the number of nearby (<100m) foreclosures before and after each regular sale. The p-value in the bottom line is the probability value for the Wald test of this difference (or the contagion discount).

corrects for all time-independent non-observable characteristics of objects, including the quality of the neighborhood. The regression equation reads:

$$ln\left(\frac{p_{ilt}}{p_{il\tau}}\right) = \alpha_{lt} - \alpha_{l\tau} + \beta'(\mathbf{X}_{it} - \mathbf{X}_{i\tau}) + \gamma(F_{it} - F_{i\tau}) + \epsilon_{ilt} - \epsilon_{il\tau}, \quad (3)$$

where τ is the date of the first transaction of property i and t is the date of the second transaction. Again the coefficient γ estimates the foreclosure discount. Identification of γ relies on properties for which the foreclosure dummy varies between the two sales. For the majority of these properties it holds that the first sale is regular and the second sale is forced ($N = 2,501$). The opposite (first sale is forced and second sale is regular) occurs only 157 times.[15]

A noteworthy feature of equation (3) is the term $\mathbf{X}_{it} - \mathbf{X}_{i\tau}$, which controls for changes in the characteristics of the property. Other papers with a repeat-sales framework commonly assume that house characteristics remain constant. The fact that house characteristics are measured by the realtor at every sale allows us to include, for instance, changes in square meters, quality or the tax treatment in our repeat sales regressions.

Table 8: Statistics repeat sales

	All repeat sales
Purchase price	251170
Sale price	236666
Square meters (purchase)	110
Square meters (sale)	109
Holding period (days)	948
One or more repeat sales (%)	
1	91.78
2	7.68
3	0.46
4	0.07
5	0.01
Repeat sales pairs	45075

Source: Statistics Netherlands and NVM.

Because the NVM dataset contains both the address and the transaction date, we can identify which properties were sold repeatedly. Our dataset includes 45,075 repeat sales pairs. Table 8 shows that most houses

[15]We also estimated equation (3) with dummies for transaction pairs forced to regular, regular to forced, and forced to forced. This gives very similar results as the specification of equation (3).

(about 92 percent) in the repeated-sales sample were sold twice. The period between the two sales is on average about 2.6 years During this period the average decline in property value was about 14,500 euro (or six percent). In contrast to earlier studies, we observe house characteristics at both the purchase and the selling date. For instance, the properties seem to be somewhat smaller at the selling date compared to the purchase date according to Table 8.[16]

Table 9: Repeat-sales regression

	I b/se	II b/se
Δ Foreclosed	-0.056***	-0.045***
	(0.003)	(0.002)
Change house char.	No	Yes
N	45075	45075
Adjusted R^2	0.309	0.488

Note: The dependent variable is the change in the log real transaction price between two transactions. The other independent variables are changes in house characteristics and corop-area-year dummies. The numbers between round brackets are robust standard errors. Legend: *: p<.05, **: p<.01 and ***: p<.001. The contagion discount gives the difference between the coefficients of the change in the number of nearby (<100m) foreclosures before and after each regular sale. The p-value in the bottom line is the probability value for the F-test of this difference (or the contagion discount).

We present the results from the repeat-sales regressions in table 9. Again, we only present the foreclosure estimates. The coefficients for the changes in house characteristics all have the expected signs. Model I and Model II present two estimates of the foreclosure discount. The difference between the two models is that we include changes in house characteristics in Model II, which reduces the estimated foreclosure discount from 5.4 percent to 4.4 percent. The higher estimate of Model I can be interpreted as a combined measure of quality changes of foreclosed properties and the pure foreclosure discount. The adjusted R^2 increases substantially from 0.309 in Model I to 0.488 in Model II. These results show that it is important to take changes of property characteristics into account when using

[16]Note that a change in square meters could reflect real (constructional) changes as well as changes in realtors' guidelines for measuring the surface area of a house.

the repeat sales model. Note that the estimate of 4.5 percent is comparable to the estimate from the hedonic regression.

We also estimated a repeat sales model excluding sales that took place within 90 days after the purchase date. Excluding these observations does not alter our results.

7 Concluding Remarks

In this paper we study the impact of forced sales on Dutch house prices. To our knowledge, we are the first to estimate reliable price effects of forced sales for a European housing market. We find that a forced sale generally leads to a price discount of five percent. A nearby foreclosure within 100 meters of a regular transaction has a negative impact on the transaction price of about 0.4 percent. These results are robust to different specifications and samples.

Our estimates of the price effects of forced sales are low relative to what other, mainly US, empirical studies find. A possible reason for this difference is that our highly detailed dataset enables us to minimize omitted variables bias. For instance, we include dozens of house and transactions characteristics and control for very small region specific time trends.

Another explanation may lie in the fact that the context in the Netherlands differs in important ways from US housing markets. Forced sales tend to be dispersed in the Netherlands, but concentrated in some local US housing markets. Additionally, Dutch foreclosed home-owners with an NHG-guarantee are obliged to ensure that their house remains well maintained and have to cooperate with the sales procedure. This obligation limits the risk that the quality of foreclosed properties declines.

We find suggestive evidence that the contagion discount is caused by a supply or price discovery effect, because nearby forced sales have a stronger effect on transaction prices of comparable houses than on prices of all neighboring regular sales.

References

BKR (2014). BKR Hypotheekbarometer. http://perskamer.bkr.nl/bkr-hypotheekbarometer-ruim-100000-consumenten-met-een-betalingsachterstand-op-de-hypotheek.

Campbell, J. Y., Giglio, S., & Pathak, P. (2011). Forced sales and house prices. *American Economic Review*, *101*, 2108–2131.

Carroll, T. M., Clauretie, T. M., & Neill, H. R. (1997). Effect of foreclosure status on residential selling price: Comment. *Journal of Real Estate Research*, *13*, 95 – 102.

Fisher, L. M., Lambie-Hanson, L., & Willen, P. S. (2014). The role of proximity in foreclosure externalities: Evidence from condominiums. *NBER Working Paper*, *20080*, 1–36.

Gerardi, K., Rosenblatt, E., Willen, P. S., & Yao, V. W. (2012). Foreclosure externalities: some new evidence. *NBER Working Paper*, *18353*.

Harding, J. P., Rosenblatt, E., & Yao, V. W. (2009). The contagion effect of foreclosed properties. *Journal of Urban Economics*, *66*, 164–178.

Immergluck, D. & Smith, G. (2006). The external costs of foreclosure: The impact of single-family mortgage foreclosures on property values. *Housing Policy Debate*, *17*, 57 – 79.

Levitt, S. D. & Syverson, C. (2008). Market distortions when agents are better informed: The value of information in real-estate transactions. *The Review of Economics and Statistics*, *90*, 599–611.

Pennington-Cross, A. (2006). The value of foreclosed property. *Journal of Real Estate Research*, *28*, 193–214.

Schuetz, J., Been, V., & Ellen, I. G. (2008). Neighborhood effects of concentrated mortgage foreclosures. *Journal of Housing Economics*, *17*, 306–319.

Shilling, J., Benjamin, J., & Sirmans, C. (1990). Estimating net realizable value for distressed real estate. *Journal of Real Estate Research*, *5*, 129–140.

Sumell, A. (2009). The determinants of foreclosed property values: Evidence from inner-city cleveland. *Journal of Housing Research*, *18*, 45–61.

Appendix A Overview of the literature

Table 10: Empirical Studies on the Foreclosure Discount

Paper	**Journal**	**Setting**	**Methodology**	**Results**
Shilling, Benjamin, Sirmans (1990)	J. of Real Estate Research	Condominium sales in Baton Rouge, Louisiana, 1985.	Hedonic regression with a sample of 62 properties.	Foreclosure discount of 24 percent.
Carroll, Clauretie, Neill (1997)	J. of Real Estate Research	Las Vegas, Nevada, 1990-1993.	Hedonic regression with a sample of 2,000 transactions. Zip code fixed effects. Dummy equal to 1 for houses in close proximity to foreclosures	Statistically insignificant foreclosure discount of 2 percent.
Pennington-Cross (2006)	J. of Real Estate Research	12,000 forced sales across the US, 1995-1999	A variation of repeat sales regression. Comparison of existing repeat sales price index with price change of foreclosed properties. The price differential is related to loan characteristics, housing market conditions and legal restrictions.	Finds a foreclosure discount of 22 percent. Discount increases in loan size and the selling time.
Sumell (2009)	J. of Housing Research	Single-family home transactions in Cleveland, Ohio, 2004-2006.	Hedonic regression with about 9,900 sales. Controls, inter alia, for condition and neigborhood characteristics.	Foreclosure discount of 50 percent. The author notes that omitted variables may bias the results.

Campbell, Giglio and Pathak (2011)	American Economic Review	Massachusetts, 1987-2009.	Hedonic regression, with census tract fixed effects. The authors differentiate between four types of forced sales, including death-related sales and bankruptcy-related sales.	The average forced sale discount is 18 percent. For bankruptcy-related forced sales it is about 3.5 percent.

Table 11: Empirical Studies on Spillover Effect

Paper	**Journal**	**Setting**	**Methodology**	**Results**
Immergluck, Smith (2006)	Housing Policy Debate	Chicago, 1997-1999.	Based on a hedonic regression. Consider the number of foreclosures close (0.125 miles) and far away (0.125-0.25 miles) and distinguish between: 1. conventional single family loans 2. government-insured single family loans 3. other foreclosures. Use latitude/longitude data to control for spatial location throughout the city.	A 0.9 percent price discount per foreclosure within 0.125 miles.

Harding, Rosenblatt and Yao (2009)	J. of Urban Economics	7 US MSAs, 1989-2007	A repeat-sales regression.	They find a 1 percent price discount per property in a 0-300 ft. radius that is in the process of foreclosure. The effect halves when a ring of 300-500 ft. is considered and is close to zero beyond 500 ft. Argue that the results indicate a physical externality.
Campbell, Giglio and Pathak (2011)	American Economic Review	Massachusetts, 1987-2009.	Hedonic regression. Specification includes the number of foreclosures one year before/after and close/far away. Additionally control for census tract fixed effects.	Report a 1 percent price discount per foreclosure that takes place 0.05 miles away. The results suggest a physical externality of forced sales.

Gerardi, Rosenblatt, Willen and Yao (2012)	NBER WP	15 largest US MSAs, 2001-2010.	Repeat-sales framework. The number of foreclosures is measured by serious delinquency (SDQ), REO, REO <1 year, REO 1-2 years close (0.10 miles) or far away (0.10-0.25 miles). Controls for census block - year fixed effects.	Find a 0.5 to 1 percent price discount per foreclosure or distressed property within a radius of 0.10 miles. Results are suggestive of a physical externality.
Fisher, Lambie-Hanson and Willen (2014)	NBER WP	Condominium transactions Boston, 1989-2011.	Repeat-sales framework. Distinguish between same condo association, same address (SASA) and same condo association, different address (SADA). Also census tract - year fixed effects.	No contagion effect for SADA condos. Strong contagion effect for SASA condos (2.5 percent per foreclosure). Results suggest physical externality.
Schuetz, Been and Ellen (2008)	J. of Housing Economics	90,000 property sales in New York City, 2002-2005.	Hedonic regression	They find a general spillover effect.

Appendix B List of variables

Variable	Description
Square meters	Logarithm of interior square meters
Cubic capacity	Logarithm of cubic capacity
Total rooms	Logarithm number of rooms
Garden surface	Logarithm of garden square meters
Sunny	Dummy equal to 1 for properties with a garden at the south side
View	Dummy equal to 1 for properties with a nice view
Wood	Dummy equal to 1 for properties next to a wood
Centre	Dummy equal to 1 for properties in the city or town centre
Busy road	Dummy equal to 1 for properties next to a busy road
Central heating	Dummy equal to 1 for properties with central heating boiler
Leasehold	Dummy equal to 1 for leasehold property
VON	Dummy equal to 1 if purchase costs are included in price (Dutch: vrij op naam)
Detached	Dummy equal to 1 for detached properties
Semi-detached	Dummy equal to 1 for semi-detached properties
Corner house	Dummy equal to 1 for corner houses
Ground floor	Dummy equal to 1 for ground floor properties
Upstairs	Dummy equal to 1 for upstairs properties
Portico flat	Dummy equal to 1 for appartment with common entrance hall
Gallery flat	Dummy equal to 1 for gallery flats
Villa	Dummy equal to 1 for villa
Luxury	Dummy equal to 1 for luxury appartments
Single-family	Dummy equal to 1 for single-family properties
Mansion	Dummy equal to 1 for mansion or town houses

Building period	Dummies for building period: ≤1905, 1906-1930, 1931-1944, 1945-1959, 1960-1970, 1971-1980, 1981-1990, 1991-2000, ≥2001
Selling month	Dummies for selling month
Maintenance interior	Dummies for interior state of maintenance: bad, bad/average, average, average/fair, fair, fair/good, good, good/excellent, excellent
Maintenance outside	Dummies for outside state of maintenance: bad, bad/average, average, average/fair, fair, fair/good, good, good/excellent, excellent

Appendix C Baseline hedonic regression

Table 13: Full results hedonic regression

	I b/se
Foreclosed	-0.054***
	(0.002)
Square meters	0.298***
	(0.007)
Cubic capacity	0.476***
	(0.008)
Total rooms	0.025***
	(0.004)
Garden surface	0.008***
	(0.000)
Sunny	0.005***
	(0.001)
View	0.015***
	(0.001)
Wood	0.041***
	(0.008)
Centre	0.012***
	(0.003)
Busy road	-0.041***
	(0.003)
Central heating	0.046***
	(0.002)
Leasehold	-0.054***
	(0.006)
VON	-0.032***
	(0.006)
Detached	0.317***
	(0.004)
Semi-detached	0.150***
	(0.003)
Corner house	0.052***
	(0.001)
Ground floor	0.028***

	(0.005)
Upstairs	-0.029***
	(0.005)
Portico flat	0.005
	(0.005)
Gallery flat	-0.009
	(0.006)
Villa	0.137***
	(0.006)
Luxury	0.100***
	(0.003)
Single-family	-0.032***
	(0.003)
Mansion	0.055***
	(0.005)
Building period: 1906-1930	-0.033***
	(0.004)
Building period: 1931-1944	-0.014*
	(0.005)
Building period: 1945-1959	-0.051***
	(0.005)
Building period: 1960-1970	-0.095***
	(0.005)
Building period: 1971-1980	-0.074***
	(0.005)
Building period: 1981-1990	-0.018***
	(0.005)
Building period: 1991-2000	0.046***
	(0.005)
Building period: after 2001	0.082***
	(0.005)
Selling month: Feb	0.002
	(0.001)
Selling month: Mar	0.005***
	(0.001)
Selling month: Apr	0.009***
	(0.001)
Selling month: May	0.010***
	(0.001)

Selling month: Jun	0.007***
	(0.001)
Selling month: Jul	0.006***
	(0.001)
Selling month: Aug	0.004**
	(0.001)
Selling month: Sep	0.003*
	(0.001)
Selling month: Oct	-0.000
	(0.001)
Selling month: Nov	-0.003*
	(0.001)
Selling month: Dec	-0.010***
	(0.001)
Maintenance interior: bad/average	0.027
	(0.015)
Maintenance interior: average	0.090***
	(0.010)
Maintenance interior: average/fair	0.090***
	(0.011)
Maintenance interior: fair	0.129***
	(0.010)
Maintenance interior: fair/good	0.153***
	(0.010)
Maintenance interior: good	0.223***
	(0.010)
Maintenance interior: good/excellent	0.270***
	(0.011)
Maintenance interior: excellent	0.273***
	(0.011)
Maintenance outside: bad/average	-0.008
	(0.020)
Maintenance outside: average	0.048***
	(0.013)
Maintenance outside: average/fair	0.049***
	(0.014)
Maintenance outside: fair	0.089***
	(0.013)
Maintenance outside: fair/good	0.100***

	(0.013)
Maintenance outside: good	0.126***
	(0.013)
Maintenance outside: good/excellent	0.141***
	(0.014)
Maintenance outside: excellent	0.139***
	(0.013)
Constant	7.732***
	(0.033)
N	749168
Adjusted R^2	0.855

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