Talking Up the Price: The Effect of the Release of School Quality Information on the Housing Market

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Abstract

This paper studies the effect of the launch of the Australian Government's "myschool" website on house prices in Victoria. We use a difference-in-difference estimator and find that the release of information about a surprisingly strong improvement in school quality raises house prices significantly. In contrast, the release of information about an equivalent decline in school quality does not affect house prices. We also use individual home sales data to estimate the effect of the release of information on high-quality or low-quality schools in the neighborhood ("good news" vs. "bad news") and find that good news increase house prices by about 4.5 percent, whereas bad news have no significant effect. Our findings suggest that the release of new information leads to inflation in the housing market because sellers (including real estate agents) talk up the price. The results are robust with respect to the common trend criterion and a range of placebo tests.

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1 Introduction

Information asymmetry may have considerable effects on the efficient allocation of resources in markets. Situations in which market participants do not possess the same amount of information have been studied extensively by economic theorists: George Akerlof, Michael Spence and Joseph E. Stiglitz received the Nobel Prize in economics for their "analysis of markets with asymmetric information" in 2001. So far, relatively little empirical evidence has been generated on the channels through which information asymmetry affect market mechanisms although the absence of perfect information may have detrimental effects on the functioning of markets and even lead to market failure. A better understanding of the functioning of markets in the absence of perfect information is particularly important if government interventions are required.

The aim of this paper is to study the effect of the publication of school quality information on house prices in the Australian state of Victoria. We use the release of information about test scores of Year 5 students through an Australian government website as a natural experiment to study the effect of a change publicly available information about the quality of schools on property prices. On 30 January 2010, the then minister of education, the Hon. Julia Gillard, MP, launched the "myschool" website (`http://www.myschool.edu.au`). The website was developed to provide information about the quality of schools in Australia and to be an "information source for parents to make informed decisions about their child's education".

To account for the possibility that market participants had some vague idea about the quality of schools even before the release of the "myschool" website, we study the effect of surprisingly large changes in school performance on house prices, using postcode-level data. We also link "myschool" data to transaction data on individual home sales to perform a suburb-level analysis of the effect of positive and negative information about school performance on house prices at the suburb level. Our empirical strategy is based on difference-in-difference estimation and we perform a number of robustness checks to test the validity of our results.

Our empirical findings reveal that the release of information about surprisingly strong increases in school quality over time raises house prices significantly. In contrast, the release of information about an equivalent decline in school quality does not affect house prices. Using individual home sales data to estimate the effect of the release of information on high-quality or low-quality schools in the neighborhood ("good news" vs. "bad news"), we find that good news increase house prices by about 4.5 percent, whereas bad news have no significant effect.

These findings suggest that the release of new information leads to inflation in the housing market because sellers (including real estate agents) appear to talk up the price. Our results are robust with respect to the common trend criterion and a range of placebo tests.

The paper is organized as follows. Section 2 provides a description of the data, the construction of the analysis sample and the definition of variables. Section 3 presents the empirical strategy of the postcode-level analysis and discusses the findings. The empirical model and the results obtained from the suburb-level analysis are presented in Section 4. In this section, we also perform a number of robustness checks. Section 5 concludes.

2 Data

We construct two data sets to perform our empirical analysis. The first data set is based on the combination of data from the Australian Property Monitors (APM) and the National Assessment Program – Literacy and Numeracy (NAPLAN) at the postcode level. Our analysis focuses on NAPLAN data for the years 2008 and 2009 because the first release of the "myschool" website contained school quality information for these two years. The APM data contain information about the monthly total value of houses being sold in a postcode area. We use this information to construct the dependent variable of our regression model. Specifically, the dependent variable is defined as the change in the smoothed (12-month average) monthly median house price and our analysis uses this information for up to three months before and after the launch of the "myschool" website.

The NAPLAN data include information about literacy and numeracy skills of students and we use this information at a postcode level to construct treatment indicators and control variables, including the number of schools and the proportion of private schools in the postcode area. We are particularly interested in positive and negative "shocks" in school performance and use information about numeracy scores to construct two treatment indicators. Specifically, we consider a surprisingly large improvement in school performance as a treatment ("positive shock") if postcodes have at least one school that experienced a *change in improvement* in numeracy relative to similar schools of at least 1 standard deviation. Similarly, we consider a surprisingly large deterioration in school performance as a treatment ("negative shock") if postcodes have at least one school that experienced a *change in deterioration* in numeracy relative to similar schools of at least 1 standard deviation. The treatment and control postcodes are presented in Figure 1.

[Figure 1 about here.]

The second part of our analysis relies on the property level data of sold properties in Victoria, published and compiled by the Australian Property Monitors (APM).[1] The data include properties sold between January, 2005 – August, 2014. We combine this data source with data from the "myschool" website for the years 2008/2009 at a suburb level. The "myschool" website publishes test school-level score categories for five different categories: reading, writing, spelling, grammar and numeracy. We use this information to define treatment variables indicating whether the five test scores of at least one school in the suburb are higher than those of similar schools in the country (we refer to the release of this information as "good news") and whether all schools in the suburb have test scores that are lower than those of similar schools in the country ("bad news"), respectively.

The total number of Victorian suburbs in the "myschool" data is 951. Due to missing information, we are only able to define a treatment indicator for good news for 680 suburbs and a treatment indicator for bad news for 566 suburbs. To increase comparability of treatment and control suburbs, we restrict our sample to neighboring suburbs, which reduces the good news sample to 270 and the bad news sample to 183 suburbs. After combining the "myschool" data with non-missing individual transaction data over the sample period February – April 2009 and February – April 2010, we obtain two analysis samples that include 12,755 individual home sales in 189 good news suburbs and 6,465 individual home sales in 123 bad news suburbs. Figure 2 presents the treatment and control suburbs for the state of Victoria and the city of Melbourne, respectively.

[Figure 2 about here.]

The 7-day moving average of the mean property price based on the individual home sales data are presented in Figure 3. We focus on the year before and after the launch of the "myschool" website. Figure 3 shows that property prices have gradually increased over the period February 2009 – January 2010 and reveals considerable seasonal variation. We will address seasonal variation in our empirical analysis by comparing the first quarter after the

[1]We thank the Australian Urban Research Infrastructure Network (AURIN) for providing us access to the APM data.

launch of the "myschool" website (Feburary 2010 – April 2010) to the same period of the previous year (February 2009 – April 2009), as indicated by the shaded area in Figure 3.

[Figure 3 about here.]

The APM data also include detailed information on the type, characteristics and features of sold properties. Type of a property is categorized as cottage, duplex, flat, house, studio, terrace, townhouse, unit and villa. Characteristics include the number of bedrooms, bathrooms and parking in a property as well as its size. Property features include the presence of air conditioner, alarm, balcony, barbeque, courtyard, ensuite, family room, fireplace, garage, heating, internal laundry, locked garage, polished timber floor, pool, rumpus room, separate dining, spa, study, sun room, tennis court, walk-in wardrobe, billiard room, sauna, views of bay, bush, city, harbor, mountain, ocean, park, river and water and whether the property has been renovated recently. We use this information to construct a range of control variables for our empirical analysis.

Figure 4 is a screen shot from the "myschool" website that shows the five different test scores of Year 3 and Year 5 students. We define our treatment and control properties based on the scores of all these modules. While scores for both 2008 and 2009 are available in our data we focus on 2009 because it appears likely that individuals align their perception (of the quality of schools) more closely with the latest information. A low number of high schools in the data and their wider catchment area (usually a few adjacent suburbs) makes it difficult to do the same analysis for Year 7 and Year 9. Our analysis focuses on Year 5. Similar results based on Year 3 test scores are largely insignificant because our parameters of interest appear to be quiet small, which makes it difficult to obtain sufficiently precise estimates from relatively small analysis samples.

[Figure 4 about here.]

Children living in a property inside the Priority Enrollment Area (PEA) of a public school are automatically eligible for a place at the school. We drop non-government schools from our analysis because this rule does not apply to them. Since the PEA of a school includes the suburb in which the school is located, we define treatment and control properties at the suburb level. We take the best scores among schools for each school year and module (if there are several schools in a suburb) and compare them with the corresponding scores of similar schools. If the former is higher than the latter for all modules, we consider properties in the suburb to experience a positive information shock ("good news").[2] In contrast, if the best scores are higher than the corresponding mean scores of similar schools for 1-4 modules, we assign the properties in the suburb to the control group. We also assign the properties in a suburb to suffer from a negative information shock if its best scores, for all the modules, are below the corresponding mean scores of similar schools ("bad news") and compare it with the same control group.

3 Postcode-Level Analysis: The Role of Surprising Changes in School Quality

3.1 Empirical Model

The analysis uses the notion of *similar schools* score to assign treatment. According to Australian Curriculum, Assessment and Reporting Authority (ACARA):

> "a school's ICSEA [socio-economic] value is used to select a group of up to 60 schools serving students from statistically similar backgrounds. Schools with students who have similar levels of educational advantage will have similar ICSEA values, even though schools in their group can be located in other parts of Australia and may have different facilities and resources. An average NAPLAN result is calculated for the 60 schools serving students with statistically similar levels of educational advantage, to enable comparison with the selected school's own NAPLAN results."[3]

Our definition of the treatment variable is based on changes in deviations from the score of similar schools. In particular, when examining "positive" shock, any postcode with at least one school with changes greater than 1 standard deviation is assigned to have received treatment. We calculate changes in deviations for school i in postcode p as follows:

$$Change_{ip} = (Score_{ip,2009} - SimScore_{i,2009}) - (Score_{ip,2008} - SimScore_{i,2008})$$

where $Score_{ip,2009}$ is the NAPLAN (numeracy) score of school i in postcode p in the year *2009* and $SimScore_{i,2009}$ is the corresponding score of schools similar to school i.

[2]The main reason behind the choice of our treatment definitions is to ensure a reasonable number of observations for both treatment and control groups in our sample.

[3]`http://www.myschool.edu.au/AboutUs/Glossary/glossaryLink`

To examine if the innovation had any information on the real estate market, we estimate the following equation:

$$\begin{aligned} Y_{pt} = & \alpha + \boldsymbol{\theta} Treatment_p + X_{ip}\beta + \delta * f(Months\_from\_SQ_t) \\ & + \gamma f(Months\_from\_SQ_t) * Treatment_p + \epsilon_{pt} \end{aligned} \tag{1}$$

where Y_{pt} is the average monthly change in (12-month moving average) log of the total value of houses or units in postcode p. The total value is based on sales and the changes are based on sales within the month (the t subscript). *Treatment* is defined as above at the postcode level and θ is the coefficient of interest. We consider varying window of up to 6 months around the release of school-quality information (the variable *Months_from_SQ*) in February, 2010. Consequently, the number of observations increase as number of months used in the analysis increases. Postcodes contiguous with the treatment postcodes are defined as the control group (see Figure 1). The control variables X include the number of schools and the proportion of private schools in the postcode.

3.2 Results

Table 1 includes the difference-in-differences estimates obtained from the postcode-level analysis. We consider a varying window between 1 and 6 months around the release of the "myschool" website. Panel A of Table 1 includes the main effects of a model in which we estimate the effect of a "positive shock" on the average change in house prices for a sample of all postcode areas with non-missing information. When using a window width of 1 month, we find that a positive shock increases the change in house prices by 0.88 percent. Increasing the window width leads to a relatively small change in the size of the estimated coefficient, which varies from 0.51 percent (6 month window) to 1.01 percent (2 month window). Due to the small size of the parameter of interest, the estimated coefficients are not always significant, which is not surprising given the relatively small size of the sample.

The estimates presented in Panel B of Table 1, which are based on neighboring treatment and control postcodes, indicate that the estimates of the treatment effect are slightly larger and somewhat more precise when we restrict our sample to increase comparability. However, the estimated coefficients are not very different from those of Panel A (between 0.54 and 1.36 percent), suggesting that a surprising increase in school performance increases the change in postcode-level house prices by about 1 percent.

Although our regression models include a range of control variables (the number of schools and the proportion of private schools in the postcode area, the average number of bedrooms, bathrooms, parking and the proportion of properties with air-conditioning, balcony and en-suite), we estimate a "Placebo" model to examine whether the model in Panel B of Table 1 only captures random noise or whether the estimated parameters may be viewed as treatment effects of the launch of the "myschool" website. We obtain Placebo estimates after shifting the event 12 months back in time, which are presented in Panel C of Table 1. The Placebo estimates indicate that the effects observed in Panel B are indeed a result of differences between treatment and control groups that occurred after the launch of the "myschool" website but not at some arbitrarily chosen point in time before the release of school quality information.

Finally, the estimates presented in Panel D of Table 1 indicate that there is no evidence for a significant effect of a negative shock on a decline in house prices. Due to this apparent asymmetry of positive and negative shocks, the following analysis will focus on the role of good and bad news in the housing market.

4 Suburb-Level Analysis: Good News vs. Bad News

4.1 Empirical Model

To examine whether good news or bad news about the quality of schools in a suburb had an effect on house prices, we estimate the following model:

$$Y_{pt} = \alpha + \theta T_p + X_{pt}\beta + \delta M_t + \gamma M_t \cdot T_p + \varepsilon_{pt} \qquad (2)$$

where Y_{pt} is the average monthly change in the (12-month moving average of the) log of the total value of houses in postcode area p at time t, T_p is the treatment group indicator, M_t is the number of months around the release of school quality information and X_{pt} is a set of control variables.

We are particularly interested in estimating the parameter γ. Our empirical strategy is based on a difference-in-difference estimator and we perform a number of robustness checks to examine the validity of our results. All models presented in the following section include suburb fixed effects.

4.2 Results

Table 2 includes the difference-in-difference (DD) estimates of the effect of good news on property prices during the first quarter after the launch of the "myschool" website. The coefficients in columns (1) and (2) indicate that good news increased house prices by about 4.5 percent during the first quarter of the release of the information. The Placebo tests in columns (3) and (4) reveal that we observe no effect if we shift our analysis 12 months back in time. Table 3 summarizes the effects of good news for up to 4 quarters after the launch of the "myschool" website. The DD estimates presented in Table 3 show that the effect is only significant at conventional levels during the first quarter of 2010. We find no effect of good news on house prices beyond the first quarter of the intervention. The corresponding Placebo estimates indicate that were no systematic differences between treatment and control suburbs at other points in time before the intervention, with exception of the fourth quarter, which we do not consider as a representative time period due to the drop in market activity and house prices at the end of each year (see Figure 3).

The estimates in Tables 4 and 5 are the corresponding effects of bad news on house prices, which are not statistically significant, suggesting that bad news are less relevant. One explanation for this result is that sellers – in particular real estate agents – who are more likely to be aware of the school quality in the neighborhood than average buyers (including those without children), have an incentive to pass on good news to their clients to increase the sales price. They have no incentive to pass on bad news to the clients because it would reduce the sales prices and therefore their return.

4.3 Robustness Checks

We perform a number of robustness checks to test the validity of our results. Figures 5 and 6 test the underlying common trend assumption of the DD estimator, which postulates that the treatment and control groups follow the same trend over time, even though they have different characteristics due to non-random assignment. Figures 5 and 6 show the effects of good and bad news for the period from February to April of each year over the time period 2006 – 2012. We use 2005 as a reference category. Figure 5 reveals that differences between treatment and control groups were insignificant during the entire period with one exception: the first quarter after the launch of the "myschool" website. This finding suggests that the observed effect of good news on house prices is indeed a result of the release of school quality information. In contrast, the corresponding effect of bad news on house prices presented in Figure 6 is insignificant throughout the entire sample period.

Because we paid particular attention to the comparison of the first quarter after the intervention to the previous year in our analysis, we also use 2009 as a reference year to examine the common trend assumption. The numbers in Table 6 include the corresponding robustness checks for the effects of good news and bad news on house prices during different quarters of the year. We find that the effect of good news on house prices during the first quarter of the launch of the "myschool" website is the only effect that is highly significant. Taken together, these robustness check provide strong evidence for an effect of good news but no effect of bad news on house prices.

5 Conclusions

Information asymmetry may have considerable effects on the efficient allocation of resources in markets. Situations in which market participants do not possess the same amount of information have been studied extensively by economic theorists. Less is known about the channels through which information asymmetry affect market mechanisms although the absence of perfect information may have detrimental effects on the functioning of markets and even lead to market failure. A better understanding of the functioning of markets in the absence of perfect information is particularly important if government interventions are required.

This paper studies the effect of the launch of the Australian Government's "myschool" website on house prices in Victoria. We use a difference-in-difference estimator and find that the release of information about a surprisingly strong improvement in school quality raises house prices significantly. In contrast, the release of information about an equivalent decline in school quality does not affect house prices. We also use individual home sales data to estimate the effect of the release of information on high-quality or low-quality schools in the neighborhood ("good news" vs. "bad news") and find that good news increase house prices by about 4.5 percent, whereas bad news have no significant effect. Our findings suggest that the release of new information leads to inflation in the housing market because sellers (including real estate agents) talk up the price. The results are robust with respect to the common trend criterion and a range of placebo tests.

Figures and Tables

Figure 1: **Treatment and Control Postcodes, Victoria**

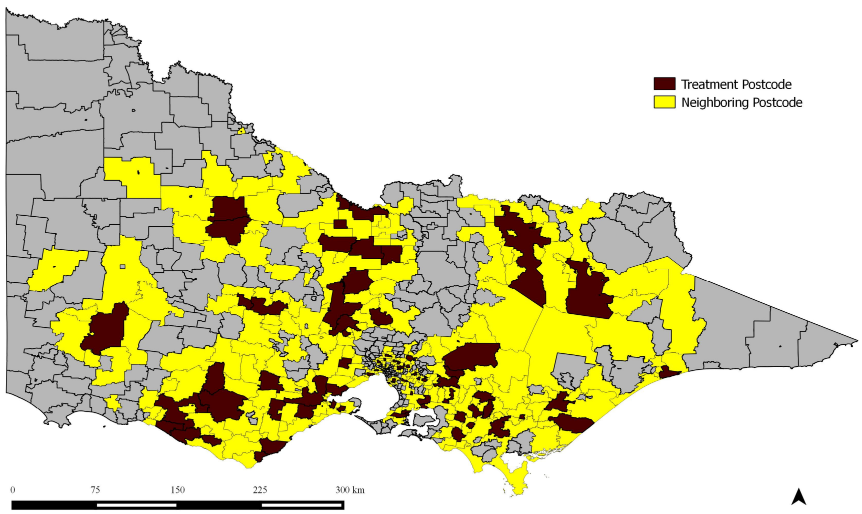


Figure 2: **Treatment and Control Suburbs, Victoria/Melbourne**

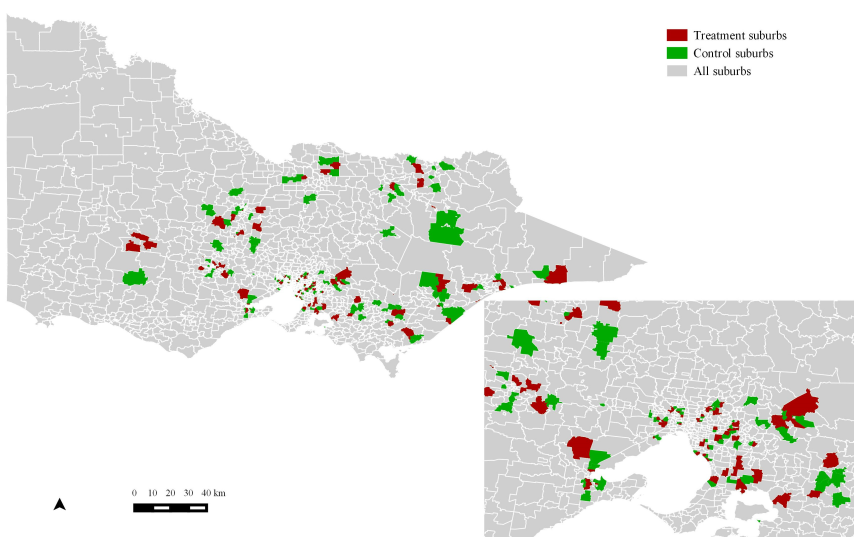
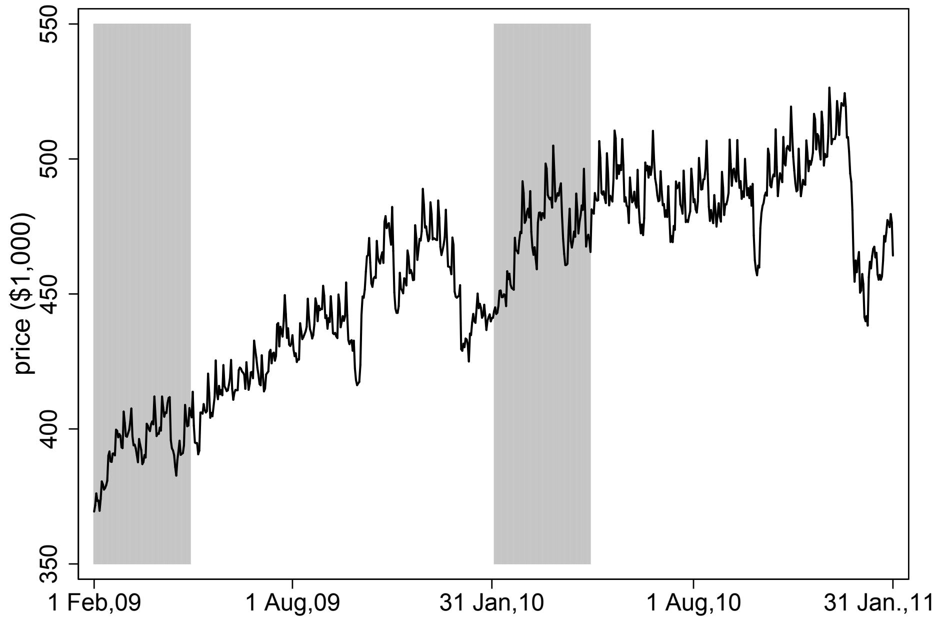
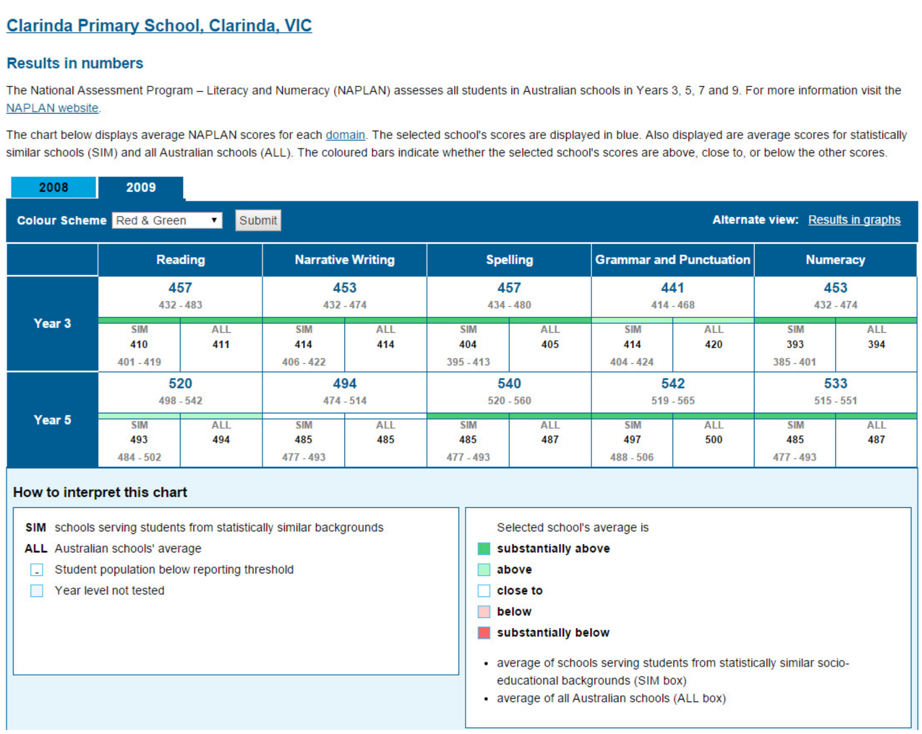


Figure 3: **Mean Property Price (7-Day Moving Average), February 2009 – January 2011**



Note: Shaded areas: February-April.

Figure 4: **Screenshot of a Typical Treatment Webpage**



Clarinda Primary School, Clarinda, VIC

Results in numbers

The National Assessment Program – Literacy and Numeracy (NAPLAN) assesses all students in Australian schools in Years 3, 5, 7 and 9. For more information visit the NAPLAN website.

The chart below displays average NAPLAN scores for each domain. The selected school's scores are displayed in blue. Also displayed are average scores for statistically similar schools (SIM) and all Australian schools (ALL). The coloured bars indicate whether the selected school's scores are above, close to, or below the other scores.

2008 2009

Colour Scheme Red & Green Submit

Alternate view: Results in graphs

	Reading		Narrative Writing		Spelling		Grammar and Punctuation		Numeracy	
Year 3	457 (432 - 483)		453 (432 - 474)		457 (434 - 480)		441 (414 - 468)		453 (432 - 474)	
	SIM 410 (401 - 419)	ALL 411	SIM 414 (406 - 422)	ALL 414	SIM 404 (395 - 413)	ALL 405	SIM 414 (404 - 424)	ALL 420	SIM 393 (385 - 401)	ALL 394
Year 5	520 (498 - 542)		494 (474 - 514)		540 (520 - 560)		542 (519 - 565)		533 (515 - 551)	
	SIM 493 (484 - 502)	ALL 494	SIM 485 (477 - 493)	ALL 485	SIM 485 (477 - 493)	ALL 487	SIM 497 (488 - 506)	ALL 500	SIM 485 (477 - 493)	ALL 487

How to interpret this chart

SIM schools serving students from statistically similar backgrounds
ALL Australian schools' average
Student population below reporting threshold
Year level not tested

Selected school's average is
substantially above
above
close to
below
substantially below

- average of schools serving students from statistically similar socio-educational backgrounds (SIM box)
- average of all Australian schools (ALL box)

TABLE 1: **The Effect of Surprising Information on House Prices**

Window width	1 Month	2 Month	3 Month	4 Month	5 Month	6 Month
Panel A: Positive shock, all postcode areas						
Treatment	0.0088**	0.0101**	0.0053	0.0065*	0.0074**	0.0051
	(0.0044)	(0.0048)	(0.0036)	(0.0034)	(0.0034)	(0.0035)
Constant	0.0096	-0.0010	0.0095	0.0101	0.0121	0.0150*
	(0.0121)	(0.0119)	(0.0108)	(0.0094)	(0.0088)	(0.0082)
Observations	528	909	1,276	1,644	2,040	2,385
R-squared	0.1945	0.1598	0.1594	0.1617	0.1646	0.1433
Panel B: Positive shock, neighboring postcodes						
Treatment	0.0116**	0.0136**	0.0076*	0.0076*	0.0078*	0.0054
	(0.0049)	(0.0055)	(0.0044)	(0.0041)	(0.0040)	(0.0040)
Constant	0.0028	-0.0207	-0.0005	0.0058	0.0077	0.0127
	(0.0185)	(0.0183)	(0.0174)	(0.0144)	(0.0133)	(0.0121)
Observations	308	533	750	960	1,202	1,407
R-squared	0.2032	0.1596	0.1655	0.1741	0.1755	0.1445
Panel C: Placebo test (shifting event 12 months back), neighboring postcodes						
Treatment	-0.0004	0.0060	-0.0019	0.0053	0.0051	0.0049
	(0.0100)	(0.0085)	(0.0068)	(0.0068)	(0.0066)	(0.0062)
Constant	0.0720***	0.0611***	0.0629***	0.0606***	0.0621***	0.0649***
	(0.0136)	(0.0101)	(0.0092)	(0.0080)	(0.0077)	(0.0079)
Observations	241	384	527	689	804	947
R-squared	0.1333	0.1131	0.1101	0.1177	0.1282	0.1106
Panel D: Negative shock, neighboring postcodes						
Treatment	-0.0065	-0.0038	-0.0079	-0.0085*	-0.0072	-0.0063
	(0.0049)	(0.0053)	(0.0049)	(0.0045)	(0.0045)	(0.0044)
Constant	0.0390***	0.0429***	0.0464***	0.0469***	0.0469***	0.0467***
	(0.0072)	(0.0078)	(0.0074)	(0.0070)	(0.0067)	(0.0065)
Observations	319	554	781	1,001	1,256	1,472
R-squared	0.1177	0.1104	0.1181	0.1195	0.1116	0.1016

Note: The dependent variable is the change in the smoothed monthly median price. All models include controls for the number of schools in the postcode, the proportion of private schools in the postcode, the number of months since dissemination of school-quality information (February 2010) and an interaction between the treatment variable and the number of months since dissemination. Control variables include the average number of bedrooms, bathrooms, parking and the proportion of properties with air-conditioning, balcony and ensuite.
Positive shock: Treatment postcodes have at least one school that experienced a *change in improvement* in numeracy relative to similar schools of at least 1 SD.
Negative shock: Treatment postcodes have at least one school that experienced a *change in deterioration* in numeracy relative to similar schools of at least 1 SD.
Standard errors (in parentheses) were clustered at the postcode level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: **The Effect of Good News on Property Prices During the First Quarter After the Release of School Quality Information**

	DD Estimates: Q1 2009 vs. Q1 2010		DD Estimates (Placebo Test): Q1 2008 vs. Q1 2009	
	(1)	(2)	(3)	(4)
DD estimate	0.0457***	0.0440***	-0.0106	-0.0092
	(0.0119)	(0.0118)	(0.0102)	(0.0101)
Adjusted R^2	0.710	0.719	0.672	0.681
F	167.05	138.24	89.26	66.98
N	12,755	12,755	12,172	12,172

Note: Estimates based on a comparison of neighboring treatment and control suburbs. Complete results are presented in Appendix-Table A.4. All models include suburb fixed effects and control for property types and property characteristics. Results in the even columns include additional control variables for property features. See Appendix-Tables A.2 and A.3 for a list of control variables. Standard errors (in parentheses) were clustered at the suburb level.

* p <0.10, ** p <0.05, *** p <0.01.

Table 3: **The Effect of Good News on Property Prices by Quarter**

DD Estimates: 2009 vs. 2010				DD Estimates (Placebo Test): 2008 vs. 2009			
Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
0.0440***	0.0089	0.0154*	-0.0099	-0.0092	0.0060	0.0116	0.0199**
(0.0118)	(0.0096)	(0.0082)	(0.0091)	(0.0101)	(0.0091)	(0.0104)	(0.0100)
[12,755]	[12,763]	[12,366]	[10,036]	[12,172]	[12,334]	[12,290]	[10,553]

Note: Estimates based on a comparison of neighboring treatment and control suburbs. Models include suburb fixed effects and control variables for property type, characteristics and features. Standard errors (in parentheses) were clustered at the suburb level. Number of observations in brackets.

* p <0.10, ** p <0.05, *** p <0.01.

Table 4: **The Effect of Bad News on Property Prices During the First Quarter After the Release of School Quality Information**

	DD Estimates: Q1 2009 vs. Q1 2010		DD Estimates (Placebo Test): Q1 2008 vs. Q1 2009	
	(1)	(2)	(3)	(4)
DD estimate	0.0227	0.0243	0.0045	0.0062
	(0.0186)	(0.0180)	(0.0140)	(0.0143)
Adjusted R^2	0.679	0.686	0.648	0.655
F	137.82	101.93	86.33	57.61
N	6,465	6,465	6,088	6,088

Note: Estimates based on a comparison of neighboring treatment and control suburbs. Complete results are presented in Appendix-Table A.5. All models include suburb fixed effects and control for property types and property characteristics. Results in the even columns include additional control variables for property features. See Appendix-Tables A.2 and A.3 for a list of control variables. Standard errors (in parentheses) were clustered at the suburb level.

* p <0.10, ** p <0.05, *** p <0.01.

Table 5: **The Effect of Bad News on Property Prices by Quarter**

DD Estimates: 2009 vs. 2010				DD Estimates (Placebo Test): 2008 vs. 2009			
Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
0.0243	0.0129	-0.0056	0.0378**	0.0062	0.0046	-0.0019	-0.0363**
(0.0180)	(0.0152)	(0.0120)	(0.0174)	(0.0143)	(0.0166)	(0.0163)	(0.0168)
[6,465]	[6,295]	[6,167]	[5,151]	[6,088]	[5,970]	[6,183]	[5,461]

Note: Estimates based on a comparison of neighboring treatment and control suburbs. Models include suburb fixed effects and control variables for property type, characteristics and features. Standard errors (in parentheses) were clustered at the suburb level. Number of observations in brackets.

* p <0.10, ** p <0.05, *** p <0.01.

Figure 5: **Test of Common Trend: Effect of Good News on Property Prices During the First Quarter After the Release of School Quality Information**

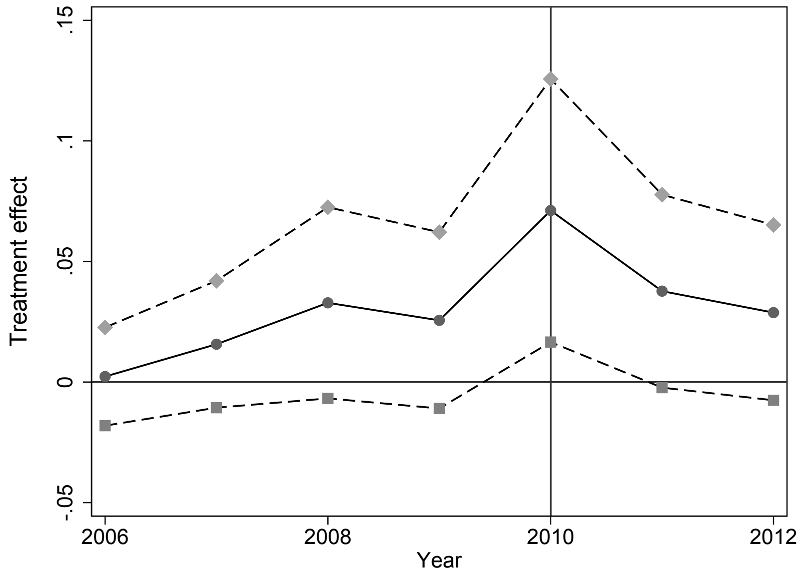


Figure 6: **Test of Common Trend: Effect of Bad News on Property Prices During the First Quarter After the Release of School Quality Information**

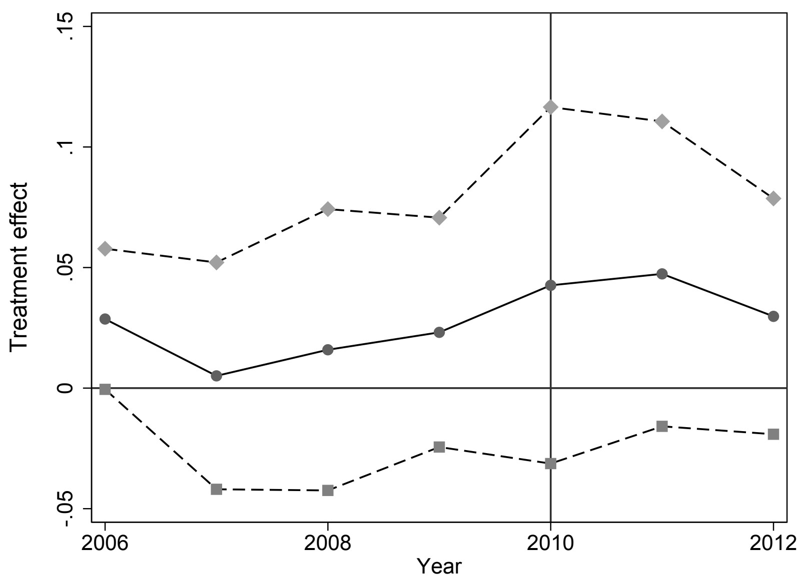


Table 6: **Robustness Check: The Effect of Good and Bad News on Property Prices by Quarter**

	Good news				Bad news			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Treatment $\times$ 2005	-0.0256	-0.0466**	-0.0431*	-0.0420*	-0.0231	-0.0124	-0.0028	0.0301
	(0.0186)	(0.0222)	(0.0245)	(0.0228)	(0.0243)	(0.0270)	(0.0348)	(0.0330)
Treatment $\times$ 2006	-0.0233	-0.0420*	-0.0439*	-0.0053	0.0055	-0.0156	-0.0168	-0.0079
	(0.0196)	(0.0213)	(0.0231)	(0.0204)	(0.0264)	(0.0301)	(0.0344)	(0.0336)
Treatment $\times$ 2007	-0.0099	-0.0131	-0.0004	-0.0019	-0.0180	-0.0021	-0.0099	-0.0080
	(0.0180)	(0.0185)	(0.0195)	(0.0151)	(0.0224)	(0.0255)	(0.0237)	(0.0258)
Treatment $\times$ 2008	0.0073	-0.0057	-0.0160	-0.0090	-0.0072	-0.0021	-0.0061	0.0393*
	(0.0142)	(0.0130)	(0.0141)	(0.0118)	(0.0200)	(0.0237)	(0.0225)	(0.0225)
Treatment $\times$ 2010	0.0455***	0.0073	0.0142	0.0020	0.0195	0.0067	-0.0081	0.0448*
	(0.0170)	(0.0136)	(0.0117)	(0.0133)	(0.0248)	(0.0215)	(0.0167)	(0.0233)
Treatment $\times$ 2011	0.0121	-0.0067	0.0062	-0.0134	0.0242	0.0078	-0.0271	0.0283
	(0.0137)	(0.0126)	(0.0129)	(0.0114)	(0.0235)	(0.0184)	(0.0192)	(0.0240)
Treatment $\times$ 2012	0.0032	-0.0163	-0.0157	-0.0064	0.0066	-0.0225	-0.0041	0.0224
	(0.0133)	(0.0151)	(0.0160)	(0.0133)	(0.0184)	(0.0155)	(0.0198)	(0.0214)
Treatment $\times$ 2013	0.0047	0.0094	0.0072	-0.0042	0.0180	0.0222	-0.0144	-0.0013
	(0.0161)	(0.0175)	(0.0169)	(0.0173)	(0.0196)	(0.0200)	(0.0386)	(0.0265)
Observations	52,569	52,340	51,094	47,463	26,609	25,974	25,791	24,132

Note: Reference year: 2009. Estimates based on a comparison of neighboring treatment and control suburbs. Model including suburb fixed effects and control variables. Standard errors (in parentheses) were clustered at the suburb level. Number of observations in brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: **Proportion of type I errors in our models**

	Good news	Bad news
Proportion	0.05	0.06
Observations	12,866	6,465

Appendix Tables

Table A.1: **Summary Statistics: Postcode Level Data**

	Control		Treatment		Differences		
	Mean	SD	Mean	SD	Mean	SE	p-value
Prop. pvt. schools	0.246	0.289	0.175	0.194	-0.071	0.005	0.000
No. of schools	2.016	1.230	2.460	1.382	0.444	0.022	0.000
Property detail							
No. of bedrooms	3.175	0.480	3.171	0.467	0.004	0.008	0.653
No. of bathrooms	1.528	0.387	1.539	0.381	0.011	0.007	0.087
No. of parking	2.166	0.639	2.128	0.616	0.038	0.011	0.000
Areasize†	27.221	295.542	28.277	232.276	1.057	4.791	0.825
Property features							
Air condition	0.205	0.230	0.198	0.229	0.007	0.004	0.077
Alarm	0.043	0.088	0.043	0.089	0.001	0.002	0.701
Balcony	0.049	0.111	0.047	0.108	0.002	0.002	0.300
BBQ	0.038	0.106	0.035	0.089	0.003	0.002	0.085
Billiard room	0.000	0.000	0.000	0.000	0.000	0.000	0.503
Courtyard	0.047	0.101	0.051	0.107	0.004	0.002	0.011
Ensuite	0.229	0.242	0.219	0.229	0.010	0.004	0.017
Family room	0.021	0.072	0.018	0.056	0.003	0.001	0.005
Fireplace	0.065	0.145	0.060	0.132	0.006	0.002	0.023
Garage	0.101	0.159	0.104	0.153	0.003	0.003	0.247
Heating	0.310	0.267	0.316	0.256	0.005	0.005	0.233
Internal laundry	0.023	0.091	0.022	0.084	0.001	0.002	0.432
Locked garage	0.078	0.138	0.088	0.146	0.010	0.002	0.000
Polished timber floor	0.083	0.143	0.084	0.138	0.000	0.002	0.865
Pool	0.012	0.063	0.011	0.057	0.001	0.001	0.357
Rumpus room	0.073	0.146	0.067	0.134	0.006	0.002	0.009
Sauna	0.000	0.000	0.000	0.000	0.000	0.000	0.570
Separate dining	0.037	0.092	0.035	0.084	0.003	0.002	0.056
Spa	0.140	0.207	0.135	0.200	0.005	0.004	0.146
Study	0.195	0.226	0.197	0.222	0.003	0.004	0.518
Sun room	0.019	0.077	0.021	0.080	0.002	0.001	0.186
Tennis court	0.001	0.018	0.001	0.018	0.000	0.000	0.700
Walk-in-wardrobe	0.105	0.166	0.104	0.159	0.002	0.003	0.586

† In 1,000 sqft.

Table A.2: **Property Detail and Type: Good News Analysis Sample**

Variable	2009			2010		
	Treatment	Control	Diff.	Treatment	Control	Diff.
Property detail						
Property size (sqm)	1,184	1,684	-500***	1,399	1,844	-444*
	(5,672)	(7,233)	(163)	(11,101)	(9,178)	(258)
Bedrooms	3.046	3.068	-0.022	3.069	3.119	-0.050**
	(0.889)	(0.778)	(0.024)	(0.828)	(0.831)	(0.024)
Bathrooms	1.525	1.525	0.000	1.544	1.543	0.000
	(0.617)	(0.600)	(0.018)	(0.628)	(0.594)	(0.019)
Parking	1.812	1.936	-0.124***	1.816	1.922	-0.106***
	(0.898)	(1.019)	(0.030)	(0.843)	(1.012)	(0.029)
Property type						
House	0.712	0.761	-0.049***	0.730	0.795	-0.065***
	(0.453)	(0.426)	(0.011)	(0.444)	(0.404)	(0.011)
Terrace	0.006	0.004	0.003	0.010	0.005	0.005**
	(0.080)	(0.059)	(0.002)	(0.098)	(0.067)	(0.002)
Townhouse	0.049	0.041	0.008	0.054	0.036	0.017***
	(0.217)	(0.198)	(0.005)	(0.226)	(0.187)	(0.005)
Unit	0.230	0.191	0.039***	0.205	0.163	0.042***
	(0.421)	(0.393)	(0.010)	(0.404)	(0.369)	(0.010)
Observations	3,445	2,828	6,273	3,603	2,879	6,482

Note: Some observations have missing property details but are included in the analysis with indicators for missing information. Standard deviations in parentheses, except for differences for which we report standard errors.

* p <0.10, ** p <0.05, *** p <0.01.

Table A.3: **Property Features: Good News Analysis Sample**

Variable	2009			2010		
	Treatment	Control	Diff.	Treatment	Control	Diff.
Air conditioning	0.219	0.209	0.010	0.215	0.210	0.005
	(0.414)	(0.406)	(0.010)	(0.411)	(0.407)	(0.010)
Alarm	0.062	0.057	0.005	0.066	0.064	0.002
	(0.241)	(0.232)	(0.006)	(0.248)	(0.244)	(0.006)
Balcony	0.045	0.035	0.010*	0.046	0.035	0.010**
	(0.207)	(0.185)	(0.005)	(0.208)	(0.184)	(0.005)
Barbeque	0.036	0.039	-0.003	0.043	0.038	0.006
	(0.186)	(0.193)	(0.005)	(0.203)	(0.190)	(0.005)
Courtyard	0.093	0.075	0.018**	0.091	0.064	0.027***
	(0.290)	(0.264)	(0.007)	(0.288)	(0.245)	(0.007)
Ensuite	0.258	0.257	0.001	0.257	0.272	-0.015
	(0.438)	(0.437)	(0.011)	(0.437)	(0.445)	(0.011)
Family room	0.031	0.030	0.001	0.027	0.039	-0.012***
	(0.173)	(0.170)	(0.004)	(0.162)	(0.194)	(0.004)
Fireplace	0.009	0.012	-0.002	0.030	0.037	-0.007
	(0.096)	(0.107)	(0.003)	(0.171)	(0.188)	(0.004)
Garage	0.129	0.126	0.003	0.131	0.129	0.003
	(0.335)	(0.331)	(0.008)	(0.338)	(0.335)	(0.008)
Heating	0.403	0.371	0.032***	0.407	0.398	0.010
	(0.491)	(0.483)	(0.012)	(0.491)	(0.490)	(0.012)
Internal laundry	0.014	0.015	-0.002	0.015	0.018	-0.002
	(0.116)	(0.122)	(0.003)	(0.123)	(0.132)	(0.003)
Locked garage	0.194	0.204	-0.010	0.141	0.134	0.007
	(0.395)	(0.403)	(0.010)	(0.348)	(0.341)	(0.009)
Polished timber floor	0.102	0.105	-0.004	0.102	0.091	0.010
	(0.302)	(0.307)	(0.008)	(0.302)	(0.288)	(0.007)
Pool	0.006	0.004	0.001	0.005	0.010	-0.005**
	(0.074)	(0.065)	(0.002)	(0.072)	(0.100)	(0.002)
Rumpus room	0.070	0.070	0.001	0.083	0.071	0.012*
	(0.256)	(0.255)	(0.006)	(0.276)	(0.257)	(0.007)
Separate dining	0.043	0.034	0.009*	0.036	0.035	0.000
	(0.202)	(0.180)	(0.005)	(0.185)	(0.185)	(0.005)
Spa	0.365	0.338	0.027**	0.178	0.179	-0.001
	(0.482)	(0.473)	(0.012)	(0.383)	(0.384)	(0.010)
Study	0.171	0.187	-0.016*	0.184	0.183	0.001
	(0.376)	(0.390)	(0.010)	(0.387)	(0.387)	(0.010)
Sun room	0.014	0.014	0.000	0.019	0.016	0.004
	(0.118)	(0.117)	(0.003)	(0.138)	(0.124)	(0.003)
Walk-in wardrobe	0.146	0.147	-0.001	0.127	0.143	-0.016*
	(0.353)	(0.354)	(0.009)	(0.333)	(0.350)	(0.009)
Observations	3,445	2,828	6,273	3,603	2,879	6,482

Note: Standard deviations in parentheses, except for differences for which we reported standard errors.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: **The Effect of Good News on Property Prices**

	DD Estimates: (Q1 2009 vs. Q1 2010)		DD Estimates (Placebo Test): (Q1 2008 vs. Q1 2009)	
	(1)	(2)	(3)	(4)
Terrace	-0.0552	-0.0547	0.0031	0.0055
	(0.0376)	(0.0369)	(0.0472)	(0.0469)
Townhouse	-0.1152***	-0.1092***	-0.1072***	-0.1005***
	(0.0162)	(0.0162)	(0.0181)	(0.0176)
Unit	-0.1949***	-0.1872***	-0.1717***	-0.1652***
	(0.0152)	(0.0149)	(0.0152)	(0.0147)
Size <=200sqm	-0.0108	-0.0050	-0.0217	-0.0177
	(0.0150)	(0.0150)	(0.0186)	(0.0181)
Size >200sqm &	0.0520***	0.0575***	0.0576***	0.0609***
<=400sqm	(0.0135)	(0.0130)	(0.0148)	(0.0141)
Size >400sqm &	-0.0136	-0.0090	-0.0192**	-0.0162*
<=600sqm	(0.0092)	(0.0085)	(0.0090)	(0.0086)
Size >900sqm	0.1144***	0.1098***	0.1099***	0.1074***
	(0.0128)	(0.0124)	(0.0124)	(0.0120)
Size missing or	-0.0464	-0.0329	-0.0450	-0.0376
implausible	(0.0770)	(0.0757)	(0.0813)	(0.0798)
1-2 bedroom	-0.1284***	-0.1240***	-0.1377***	-0.1341***
	(0.0098)	(0.0098)	(0.0094)	(0.0094)
5+ bedroom	0.1664***	0.1361***	0.1854***	0.1609***
	(0.0143)	(0.0140)	(0.0145)	(0.0142)
Missing bedroom	-0.0611***	-0.0587***	-0.0489***	-0.0464***
	(0.0118)	(0.0117)	(0.0143)	(0.0142)
2+ bathroom	0.2069***	0.1584***	0.2119***	0.1840***
	(0.0115)	(0.0112)	(0.0111)	(0.0109)
Missing bathroom	0.0941***	0.0917***	0.0880***	0.1018***
	(0.0158)	(0.0160)	(0.0174)	(0.0177)
3+ parking	0.0583***	0.0518***	0.0701***	0.0617***
	(0.0095)	(0.0091)	(0.0102)	(0.0098)
Missing/no parking	-0.0601***	-0.0340***	-0.0467***	-0.0271***
	(0.0101)	(0.0100)	(0.0095)	(0.0101)
After	0.1395***	0.1378***	0.0062	-0.0059
	(0.0079)	(0.0079)	(0.0081)	(0.0083)
DD estimate	0.0457***	0.0440***	-0.0106	-0.0092
	(0.0119)	(0.0118)	(0.0102)	(0.0101)
Constant	5.7486***	5.7167***	5.7407***	5.7069***
	(0.0079)	(0.0099)	(0.0095)	(0.0104)
Adjusted R^2	0.710	0.719	0.672	0.681
F	167.05	138.24	89.26	66.98
N	12,755	12,755	12,172	12,172

Note: Clustered standard errors in parentheses. Number of observations in brackets. Reference group includes houses with sizes between >600sqm & <=900sqm, 3-4 bedrooms, 1 bathroom and 1-2 parking. Models include suburb fixed effects. The even number column results additionally rely on property features (not presented).

* p <0.10, ** p <0.05, *** p <0.01.

Table A.5: **The Effect of Bad News on Property Prices**

	DD Estimates: (Q1 2009 vs. Q1 2010)		DD Estimates (Placebo Test): (Q1 2008 vs. Q1 2009)	
	(1)	(2)	(3)	(4)
Terrace	-0.0359	-0.0401	-0.1106*	-0.1247**
	(0.0669)	(0.0639)	(0.0656)	(0.0621)
Townhouse	-0.1411***	-0.1368***	-0.1599***	-0.1605***
	(0.0319)	(0.0312)	(0.0337)	(0.0329)
Unit	-0.2255***	-0.2176***	-0.2481***	-0.2406***
	(0.0258)	(0.0252)	(0.0261)	(0.0255)
Size <=200sqm	0.0220	0.0233	0.0295	0.0262
	(0.0228)	(0.0224)	(0.0265)	(0.0264)
Size >200sqm &	0.0759***	0.0803***	0.0926***	0.0931***
<=400sqm	(0.0217)	(0.0200)	(0.0178)	(0.0167)
Size >400sqm &	-0.0258*	-0.0241*	-0.0192	-0.0182
<=600sqm	(0.0150)	(0.0139)	(0.0146)	(0.0136)
Size >900sqm	0.0568***	0.0545***	0.0839***	0.0838***
	(0.0175)	(0.0176)	(0.0176)	(0.0172)
Size missing or	-0.0743	-0.0645	-0.1026	-0.0929
implausible	(0.1166)	(0.1153)	(0.1191)	(0.1194)
1-2 bedroom	-0.1601***	-0.1555***	-0.1639***	-0.1552***
	(0.0149)	(0.0150)	(0.0177)	(0.0172)
5+ bedroom	0.2038***	0.1814***	0.2171***	0.1929***
	(0.0240)	(0.0258)	(0.0275)	(0.0298)
Missing bedroom	-0.0156	-0.0138	-0.0010	0.0009
	(0.0209)	(0.0210)	(0.0232)	(0.0229)
2+ bathroom	0.2040***	0.1749***	0.2130***	0.1992***
	(0.0123)	(0.0145)	(0.0134)	(0.0146)
Missing bathroom	0.0378*	0.0484**	0.0440*	0.0637***
	(0.0208)	(0.0208)	(0.0240)	(0.0243)
3+ parking	0.1010***	0.0967***	0.0712***	0.0667***
	(0.0136)	(0.0136)	(0.0136)	(0.0138)
Missing/no parking	-0.0343***	-0.0172	-0.0405**	-0.0292*
	(0.0130)	(0.0137)	(0.0159)	(0.0164)
After	0.1758***	0.1747***	-0.0206**	-0.0340***
	(0.0113)	(0.0115)	(0.0084)	(0.0096)
DD estimate	0.0227	0.0243	0.0045	0.0062
	(0.0186)	(0.0180)	(0.0140)	(0.0143)
Constant	5.7885***	5.7537***	5.8019***	5.7721***
	(0.0118)	(0.0145)	(0.0138)	(0.0147)
Adjusted R^2	0.679	0.686	0.648	0.655
F	137.82	101.93	86.33	57.61
N	6,465	6,465	6,088	6,088

Note: Clustered standard errors in parentheses. Number of observations in brackets. Reference group includes houses with sizes between >600sqm & <=900sqm, 3-4 bedrooms, 1 bathroom and 1-2 parking. Models include suburb fixed effects. The even number column results additionally rely on property features (not presented).

* p <0.10, ** p <0.05, *** p <0.01.