RUHR ECONOMIC PAPERS

John Haisken-DeNew
Syed Hasan
Nikhil Jha
Mathias Sinning

Unawareness and Selective Disclosure: The Effect of School Quality Information on Property Prices

rwi

#667

Imprint

Ruhr Economic Papers

Published by

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

RWI Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

Editors

Editorial Office

Ruhr Economic Papers #667

Responsible Editor: Jochen Kluve

ISSN 1864-4872 (online) – ISBN 978-3-86788-774-8

Ruhr Economic Papers #667

John Haisken-DeNew, Syed Hasan,
Nikhil Jha, and Mathias Sinning

Unawareness and Selective Disclosure: The Effect of School Quality Information on Property Prices

Bibliografische Informationen der Deutschen Nationalbibliothek

Die Deutsche Bibliothek verzeichnet diese Publikation in der deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über: *http://dnb.d-nb.de* abrufbar.

Das RWI wird vom Bund und vom Land Nordrhein-Westfalen gefördert.

http://dx.doi.org/10.4419/86788774
ISSN 1864-4872 (online)
ISBN 978-3-86788-774-8

John Haisken-DeNew, Syed Hasan, Nikhil Jha, and
Mathias Sinning[1]

Unawareness and Selective Disclosure: The Effect of School Quality Information on Property Prices

Abstract

The Australian Government launched the My School website in 2010 to provide standardised information about the quality of schools to the Australian public. This paper combines data from this website with home sales data for the state of Victoria to estimate the effect of the publication of school quality information on property prices. We use a difference-in-difference approach to estimate the causal effect of the release of information about high-quality and low-quality schools relative to medium-quality schools in the neighborhood and find that the release of information about high-quality schools increases property prices by 3.6 percent, whereas the release of information about low-quality schools has no significant effect. The findings indicate that many buyers are unaware of the relevance of school quality information and that real estate agents pursue a strategy of disclosing information about high-quality schools to increase the sales price. Results from a survey of Victorian real estate agents provide evidence in favor of this strategy.

JEL Classification: D82, D84, I24, R31

Keywords: School quality; housing markets; information asymmetry; public policy evaluation; difference-in-difference estimation

January 2017

1 John Haisken DeNew, University of Melbourne and IZA Bonn; Syed Hasan, Australian National University; Nikhil Jha, University of Melbourne; Mathias Sinning, Australian National University, IZA Bonn and RWI. *– We thank Deborah Cobb-Clark, Tim Moore, Michael Shields, Haishan Yuan, participants of the Australian Conference of Economists 2016, the Labour Econometrics Workshop 2016 and seminar participants at the Crawford School of Public Policy and the University of Canberra Institute for Governance and Policy Analysis for helpful comments. Mathias Sinning gratefully acknowledges the financial support from the Australian Research Council (DP150104247).* *– All correspondence to: Mathias Sinning, Crawford School of Public Policy, College of Asia and the Pacific, JG Crawford Building #132, Lennox Crossing, The Australian National University, Canberra ACT 2601, e-mail: mathias.sinning@anu.edu.au*

1 Introduction

Adverse selection has important implications for the functioning of markets. In particular, if sellers are unable to convey credible information about the quality of a good to potential buyers, the market will be dominated by low-quality goods because sellers receive no compensation for offering high-quality goods (Akerlof, 1970). Unfortunately, relatively little is known about the information disclosure strategies that sellers might pursue to address adverse selection problems, although sellers of high-quality goods have a strong incentive to disclose information, whereas sellers of low-quality goods may prefer to withhold information. Understanding the consequences of a seller's ability to disclose information selectively may be particularly relevant from a policy perspective.[1]

The policy implications that result from selective information disclosure also depend on how much buyers know. The literature on asymmetric information typically assumes that buyers know the distribution, but not the exact value, of a relevant unknown characteristic of a good (Li et al., 2016). This literature, including the strand that studies situations in which sellers disclose verifiable information selectively to influence the actions of buyers (Grossman, 1981; Milgrom, 1981; Milgrom & Roberts, 1986), typically assumes that buyers are rational. In contrast, more recent work takes into account that buyers are often unaware of the relevance of the characteristics of a good or even of the existence of such characteristics (Milgrom, 2008). The unawareness literature usually dismisses rationality and assumes a non-common prior between sellers and buyers.[2]

The aim of this paper is to study the effect of the release of school quality information on property prices. A few studies have examined the role of school quality information in housing markets and produced rather mixed results.[3] Figlio & Lucas (2004) investigate

[1] Milgrom (2008) quotes a remarkable example from the pharmaceutical industry, the case of Merck's arthritis drug, Vioxx. The drug doubled the risk of heart attacks but there were no studies to confirm this although the side effect was *suspected* by scientists for years before the drug was banned. The case highlighted the need for a change in testing and reporting requirements.

[2] Unawareness has been linked to a range of areas of consumer behavior in recent years (DellaVigna & Malmendier, 2004; Eliaz & Spiegler, 2006, 2011; Gabaix & Laibson, 2006; Filiz-Ozbay, 2012; Auster, 2013; Zhou, 2008; Mullainathan et al., 2008; Shapiro, 2006; Spiegler, 2006).

[3] In contrast, considerable work has been done on the effect of school quality on house prices. Davidoff & Leigh (2008) use Australian data and find that a five percentage point increase in test scores is associated with a 3.5 percent increase in house prices. The authors also provide an overview of the literature, which has produced similar results for the UK and the US.

whether the housing market in Florida responds to the information incorporated in state-administered school grades. They observe an information effect on house prices and find that this effect diminishes over time. Imberman & Lovenheim (2016) study the effect of the release of school and teacher quality information in Los Angeles and find that the release of their quality measures does not affect house prices. Carrillo et al. (2013) provide the first evidence on strategic information disclosure in housing markets but conclude that this behavior has no effect on house prices. Against this background, we are particularly interested in the following. How does the public release of school quality information affect property prices? Is the effect of receiving information about high-quality schools as important as the effect of receiving information about low-quality schools? Are buyers unaware of the role of school quality information in shaping property prices? Does this enable real estate agents to pursue a strategy of disclosing school quality information selectively?

Our analysis takes advantage of the release of school quality information through an Australian government website, the so-called *My School* website, which allows us to study the effect of a change in publicly available information about the quality of schools on property prices in the Australian state of Victoria. On 28 January 2010, the then minister of education, the Hon. Julia Gillard, MP, launched the *My School* website (`http://www.myschool.edu.au`). The website was developed to provide standarized information about the quality of schools to the Australian public. We link the data from the *My School* website (as published on 28 January 2010) to transaction data on individual home sales for the state of Victoria to estimate the effect of school quality information on property prices. A difference-in-differences approach is used to estimate the effect of the release of information about high-quality schools ("good news") or low-quality schools ("bad news") relative to medium-quality schools.

We make several contributions to the literature. First, we study the effect of the release of information about high-quality schools and low-quality schools on property prices. We cannot simply assume that the effect of receiving good news is as important as the effect of receiving bad news. Second, it appears likely that real estate agents are better informed about the quality of schools than home buyers because they undertake many transactions, whereas home buyers are typically only involved in a single transaction. If buyers are unaware of the relevance of school quality information and if real estate agents only disclose information about high-quality schools, then we would expect a relatively large (positive) effect of good news and a relatively small (negative) effect of bad news on property prices. Therefore, our analysis may allow us to draw inferences about the extent to which buyers are unaware about the importance of school quality information. Empirical evidence on unawareness of publicly available information is scarce. Finally, we provide direct evidence from a survey of real estate agents to ascertain whether or not real estate agents actively pursue a strategy of selective information disclosure. Evidence on this mechanism is important because it has widespread applications. Depending on the context, selective information disclosure may justify the need for government interventions (such as consumer protection laws or mandatory disclosure rules). To date, there is no evidence that establishes a link between school quality information disclosure strategies of real estate agents and property prices.

We find that the release of good news increases property prices by 3.6 percent. The effect remains significant after controlling for school quality, indicating that our treatment captures an information effect rather than a school quality effect. Our results are robust with respect to the common trend criterion and a range of robustness checks. The effect of the release of bad news is not statistically significant, suggesting that the release of seemingly neutral information about the quality of schools (i.e. information ranging from low school quality to high school quality) may lead to an increase in property prices. Our results also suggest that many buyers are unaware of the relevance of school quality information because they pay a higher price if they receive good news but they do not respond to bad news. Finally, our survey of real estate agents confirms that most real estate agents mention high-quality schools in the neighborhood to potential buyers but do not disclose information about low-quality schools.

The paper is organized as follows. Section 2 provides an overview of the institutional setting. Section 3 includes a description of the data and a discussion of our empirical strategy. The results are presented in Section 4. Section 5 concludes.

2 Institutional Setting

The Australian education system is much like that in other developed countries, such as the US and the UK. Schooling is compulsory from age 6 to 17 and the focus is on general education.[4] And although non-public (Catholic or Independent) schools operate across the country, about 70 percent of all schools are public schools (Australian Bureau of Statistics, 2011). More importantly, admission in public schools is generally available only for residents within the school zone. States and Territories are responsible for schooling and determine regulations and school policies.[5]

Prior to the introduction of the National Assessment Program for Literacy and Numeracy (NAPLAN) in 2008, States and Territories used disparate curricula and assessments. The nation-wide testing of all students in grades 3, 5, 7 and 9 via NAPLAN tests set the stage for providing reliable and comparable information about schools. State-wide tests were not uncommon prior to the launch of the *My School* website but school rankings for the state of Victoria were limited to the printed *Good Schools Guide Vic* from 1999 to 2010.[6]

With the nationwide introduction of the *My School* system in 2010, the website may have released potentially *new* information into the Victorian market, over and above that of the printed guide. The *My School* website provides easily interpretable information by presenting scores, bands or graphs. A unique feature of the website is that in addition to the information regarding the school, it also provides comparable information for "similar" schools in the country. The definition of similar schools is based on a range of

[4]Students may leave school when they turn 15 but they must be engaged in vocational education or training.

[5]Although the Federal Government provides funding for schools, it has limited legislative authority.

[6]From the publisher's own summary: "*This authoritative and long-standing guide contains invaluable information that has been helping parents make the difficult decision of choosing the right school for their child since 1999. It is truly unique and comprehensive as it covers every metropolitan and rural secondary school in Victoria - government, independent, Catholic and boarding! With independent and objective school profiles, parents can easily and quickly compare schools on many different aspects of the student's study experience; from fees, enrolment size, gender balance and uniform policy through to curriculum, post-secondary destinations, co-curricular activities and support staff, VCE* [Victorian Certificate of Education] *performance and scholarship information. This is information that cannot be found anywhere else! To further assist, the guide also contains boarding school profiles, contact details, a quick reference table comparing each school's characteristics and performance, a 'schools by region' section as well as helpful advice on researching and choosing a school.*"

indicators that are used to create an Index of Community Socio-Educational Advantage (ICSEA).[7] ICSEA describes the average educational advantage that students have in their school. The index was created to determine similar schools to make educational achievement comparisons fair.

We are interested in studying whether the *My School* website provided new information that was valuable enough to affect property prices. The *My School* website publishes school-level test scores for five different categories: reading, writing, spelling, grammar and numeracy. The test scores are placed on a scale from approximately 0 to 1,000 and it is possible for a test score to be negative. The website also provides information about test scores of students in similar schools and test scores of students in all schools. Figure 1 reproduces a screen shot from the *My School* website that shows the five test scores of Year 3 and Year 5 students.

[Figure 1 about here.]

We perform our analysis at a suburb level because the *My School* website allows users to search for schools by suburb and because we observe property prices at a suburb level. Suburbs have about the same size as school zones but the borders of suburbs and school zones are not necessarily consistent. The *My School* website does not provide information about school zones and while buyers usually know the suburb in which a property is located, it appears less likely that they are aware of the exact location of school zone borders. Nevertheless, in order to study the consequences of differences between suburbs and school zones on our results, we perform a robustness check based on a restricted sample in which suburbs are located within school zones to ensure that suburbs do not share the same school zone.

We use the test scores provided by the *My School* website to define two treatments: "good news": all five test scores of at least one school in the suburb are higher than those of similar schools in the country, and "bad news": all five test scores of all schools in

[7] The index captures information about parental occupation, parental education, the location of schools (such as regional, remote, etc.) and the proportion of Indigenous students.

the suburb have test scores that are lower than those of similar schools in the country.[8] Our control group consists of all suburbs that receive neither good news nor bad news according to this definition. To make treatment and control suburbs more comparable, we restrict our analysis to *neighboring* treatment and control suburbs that are located in the same postcode area. Moreover, our analysis focuses on public schools because children living in a property inside the school zone of a public school are automatically eligible for a place in the school. We drop non-public schools from our analysis because this rule does not apply to them. Finally, our analysis focuses on test scores of Year 5 students. The estimates obtained from a similar analysis based on test scores of Year 3 students are somewhat smaller, suggesting that school choices are more relevant at higher grades. Unfortunately, we are unable to confirm this trend by performing a similar analysis for Year 7 and Year 9 because of the low number of high schools in the data and their wider school zones (usually a few adjacent suburbs).

3 Data and Empirical Strategy

3.1 Data

Our analysis is based on transaction data of sold properties in Victoria, published and compiled by the Australian Property Monitors (APM).[9] The data include properties sold between January, 2005 – August, 2014. Figure 2 reports the mean property price (7-day moving average) for the period February 2009 – January 2011. We are particularly interested in the years before and after the launch of the *My School* website when estimating the effect on property prices. Figure 2 reveals considerable seasonal variation and shows that property prices have gradually increased over the period February 2009 – January 2011. We will address seasonal variation in our empirical analysis by comparing the first three months after the launch of the *My School* website (February 2010 – April 2010) to the same period of the previous year (February 2009 – April 2009), as indicated by the

[8] The definition of these treatments takes into account that parents are able to choose the best school in a suburb/school zone for their children.

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

shaded areas in Figure 2.

[Figure 2 about here.]

We combine the property data with data from the *My School* website for the year 2009 at a suburb level.[10] The total number of Victorian suburbs in the *My School* data is 951. Due to missing information, we are only able to define treatment indicators for good news and bad news for 624 suburbs. To increase comparability of treatment and control suburbs, we restrict our sample to *neighboring* suburbs. We define neighboring suburbs as suburbs that are located in the same postcode area. After combining the *My School* data with non-missing home sales data over the sample periods February – April 2009 and February – April 2010, we obtain two main analysis samples that we call the "good news sample" and the "bad news sample". The good news sample includes 12,674 individual home sales in 170 (67 treatment + 103 control) suburbs and the bad news sample includes 5,994 individual home sales in 115 (43 treatment + 72 control) suburbs. Figure 3 depicts the geographic location of the treatment and control suburbs of the good news sample.

[Figure 3 about here.]

The means and standard deviations reported in Table 1 provide an overview of test scores and property prices in our two main analysis samples. Since our definition of good news is based on information about high-quality schools, average test scores in the treatment suburbs of the good news sample are consistently higher than those of the control sample although the differences are not always statistically significant. Similarly, average test scores in the treatment suburbs of the bad news sample are lower than those of the control sample but the differences in the bad news sample are statistically significant.

[10]The original version of the *My School* website contained test scores for 2008 and 2009. Our analysis focuses on 2009 because it appears likely that individuals align their perceptions more closely with the latest information.

We observe a \$19,000 gap in property prices between treatment and control suburbs of the good news sample before the launch of the *My School* website, indicating that property prices in neighborhoods with high-quality schools were already somewhat higher before the intervention. In contrast, property prices in treatment and control suburbs of the bad news sample were about the same before the launch of the website. Property prices in treatment suburbs of the bad news sample were even a bit higher (about \$5,000) than those of the control suburbs but this difference is not statistically significant. After the launch of the website, the gap in property prices in the good news sample increased to about \$64,000, indicating that property prices in treatment and control suburbs of the good news sample did not follow the same time trend. In contrast, the gap in property prices in the bad news sample after the intervention remained almost unchanged, suggesting that property prices in treatment and control suburbs of the bad news sample did follow the same time trend.

[Table 1 about here.]

In addition to the two analysis samples discussed above, we use extended samples for the period 2005 – 2013 to perform a range of robustness checks. Our extended analysis samples include a slightly larger number of suburbs because we observe individual transaction data for additional suburbs before 2009 and after 2010. As a result, we obtain an extended good news sample that includes 215 (112 treatment + 103 control) suburbs and 52,910 individual home sales over the period 2005 – 2013. Our extended bad news sample includes 130 (53 treatment + 77 control) suburbs and 26,138 individual home sales over this period.

Finally, the APM data also contain a large set of property characteristics, including property type (cottage, duplex, flat, house, studio, terrace, townhouse, unit and villa), a set of variables describing the size of the property (size in square meters, the number of bedrooms, bathrooms and parking), and a range of property features, including 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, and walk-in wardrobe.

We use this information to construct a set of control variables for our empirical analysis. Appendix-Table A.1 includes summary statistics for the property characteristics of the good news sample.

3.2 Empirical Strategy

To estimate the effect of the launch of the *My School* website on property prices, a difference-in-difference (DD) model is employed. The DD model is based on comparing the difference in property prices between treatment and control suburbs before and after the launch of the *My School* website. The identifying assumption of this approach is that the difference in property prices between treatment and control suburbs would have remained constant in the absence of the launch of the *My School* website. The DD model can be written as follows:

$$Y_{ist} = \delta_0 + \delta_1 After_t + \delta_2 After_t \times Treatment_s + X_{ist}\delta_3 + \phi_s + \varepsilon_{ist}, \quad (1)$$

where Y_{ist} is the (logarithm of) the average property price of transaction i in suburb s ($s = 1, \ldots, S$) at time t ($t = 2009, 2010$), $After_t$ is an indicator variable that takes on the value one for the period after the launch of the *My School* website, and zero otherwise, $Treatment_s$ is the treatment indicator (good news or bad news), and X_{ist} is the set of control variables mentioned above. The model includes suburb fixed effects (ϕ_s) to net out time-invariant variables (such as the number of public and private schools in a suburb). In our analysis, we will compare the first quarter after the launch of the *My School* website (February – April 2010) to the same period 12 months earlier (February – April 2009) to avoid problems related to seasonality. We will refer to these periods as "Q1 2009" and "Q1 2010". We will also compare the second quarter after the launch of the website (May – July 2010) to the same period 12 months earlier (May – July 2009) and refer to these periods as "Q2 2009" and "Q2 2010". Similarly, we will compare "Q3 2009" to "Q3 2010" and "Q4 2009" to "Q4 2010".

We cannot test our identifying assumption directly but we are able to perform a range of placebo tests by estimating the same model at other points in time. For example, we would expect to observe no effect if we would shift our model 12 months back in time and re-estimate equation (1) for the time periods February 2008 – April 2008 ("Q1 2008") and February 2009 – April 2009 ("Q1 2009") because property prices in treatment and control suburbs should have followed the same time trend in the absence of the launch of the *My School* website. We use our extended analysis samples for the time period 2005 – 2013 to estimate the following model, in which we interact the treatment indicator with indicator variables for each year, using 2009 as the reference year:

$$Y_{ist} = \alpha + \sum_{t \in T} \beta_t Year_t \times Treatment_s + X_{ist}\gamma + \phi_s + \lambda_t + \nu_{ist}, \qquad (2)$$

where $T = \{2005, \ldots, 2008, 2010, \ldots, 2013\}$, $Year_t$ is an indicator variable for the respective time period and λ_t is a time fixed effect. Similar to equation (1), we will estimate this model by comparing one of the four quarters after the launch of the *My School* website to the respective quarters in 2005 – 2013 (using the relevant quarter in 2009 as the reference period).

4 Results

This section presents our empirical findings. Section 4.1 discusses the results obtained from a DD model that does not control for school quality because we are interested in comparing our DD estimates to a range of placebo estimates, which involve analyzing property prices during a period before the start of the collection of NAPLAN school quality data in 2008. We discuss the placebo estimates in Section 4.2. Section 4.3 presents the results of a DD model including control variables for school quality (our preferred specification). Section 4.4 discusses a number of robustness checks. The results obtained from a survey of real estate agents are presented in Section 4.5.

4.1 Difference-in-Difference Estimates

Table 2 includes the DD estimates of the effect of good news and bad news on property prices during the first quarter after the launch of the *My School* website. The DD estimates in columns (1) and (2) indicate that good news increased property prices by around 4.5 percent during the first quarter of the release of the information. In contrast, the DD estimates in columns (3) and (4) reveal that the effect of bad news on property prices is not significant. These findings are consistent with the hypothesis that sellers – in particular real estate agents – who are more likely to be aware of the school quality in the neighborhood than buyers, have an incentive to pass on good news to their clients to increase the sales price. It appears likely that real estate agents have no incentive to pass on bad news to the clients because it would reduce the sales price and therefore their private return through the reduced commission. We provide empirical evidence in favor of this hypothesis in Section 4.5. The findings presented in Table 2 also suggest that buyers appear to be unaware of the relevance of school quality information because they pay a higher price if they receive good news but they do not respond to bad news.

[Table 2 about here.]

Table 3 summarizes the effect of good news for up to four quarters after the launch of the *My School* website. Each model is based on a comparison of the respective quarter after the launch of the website with the same period 12 months earlier. The DD estimates presented in Table 3 show that the effect is only significant during the first quarter of 2010. We do not find a significant effect of good news on property prices beyond the first quarter of the intervention. We also find no evidence for an effect of bad news on property prices (all bad news coefficients are insignificant).

[Table 3 about here.]

The temporary nature of the effect of good news on property prices may appear counterintuitive, given that we would expect that markets absorb information through permanent price adjustments (or at least until new information emerges). Figure 4 offers a plausible explanation for the temporary effect of school quality information on property prices: people seem to lose interest in the *My School* website over time. Figure 4 summarizes the web search interest in "my school" in Australia for the period January

2009 – January 2013 obtained from the portal Google Trends. The relative frequencies reveal considerable interest in the *My School* website when it was launched on 28 January 2010 and some (relatively moderate) interest during the first few weeks after the launch.

[Figure 4 about here.]

The web search interest remained low for the rest of the year and only spiked again in January 2011 when the *My School* website was updated for the first time. However, interest in the update was much lower compared to the original interest in the website at the launch in 2010. When the website was updated a second time in January 2012, almost no interest was registered. Given the dramatic decline in web search interest beyond the first few weeks after the launch of the *My School* website, it does not seem to be surprising that we do not observe a continuing effect of school quality information on property prices. Either people simply did not know of the existence of the website, or they discounted the value of the information contained therein.

Following up on the idea of information discounting, the printed *Good Schools Guide Vic* (see Section 2) was the only available school ranking for the state of Victoria from 1999 to 2010. For price changes to be reflected in the market, the website information must have provided an information innovation of value, at least for a short time. Previous information, available also in the guide, had already been capitalized into property prices. Thus when the website was made publicly available, there may have been an apparent innovation in information, but over time, the innovation was not sustained (as shown by the strongly diminishing interest in Google hits to the website).

4.2 Placebo Effects

We estimate a number of placebo effects to test the stability of the results presented in Section 4.1. 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 years 2005 – 2013. We use 2009 as a reference category to be consistent with the results presented in Tables 2 and 3.

[Figure 5 about here.]

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 *My School* website. The figure shows the point estimates and confidence intervals. From 2005 to 2013, only in 2010 is the point estimate significantly different from zero. This finding suggests that the observed effect of good news on property prices is directly attributable to the launch of the website. In contrast, the corresponding effect of bad news on property prices presented in Figure 6 is insignificant throughout the entire sample period (the confidence intervals cross the treatment effect zero line).

[Figure 6 about here.]

The numbers in Table 4 include the corresponding results for the effects of good news and bad news on property prices during different quarters of the year. We provide a comprehensive grid of all quarters over all years from 2005 to 2013. We find that the effect of good news on property prices during the first quarter of the launch of the *My School* website (the bold coefficient of Q1 of the good news estimates) is the only effect that is highly significant. The coefficient indicates that the release of information about high-quality schools led to an increase in sales prices of Victorian homes by 4.66 percent. The corresponding effect of bad news on property prices (0.63 percent, the bold coefficient of Q1 of the bad news estimates) is not significant. Taken together, these estimates provide strong evidence for a significant effect of good news, but no effect of bad news on property prices.[11]

[Table 4 about here.]

[11] We also tried to shift our original DD model 12 months back in time to re-estimate equation (1) for Q1 2008 and Q1 2009. As expected, the placebo effect obtained from this model is insignificant, confirming that there were no systematic differences between treatment and control suburbs before the intervention.

4.3 School Quality vs. School Quality Information

So far, our analysis has focused on estimating a treatment effect that may capture both a school quality effect and the effect of new information about the quality of schools on property prices. We are unable to control for the quality of schools in our placebo tests because NAPLAN data are not available before 2008. To net out school quality levels, we re-estimate equation (1) and include school quality measures (student test scores) as additional control variables in our model. Table 5 reveals that our good news effects are unsurprisingly slightly smaller when we control for school quality. Specifically, after including test scores in our model, the additional effect of information about high-quality schools according to the *My School* website on property prices is only 3.6 percent. However, this information effect is still highly significant, even after controlling for school quality.

[Table 5 about here.]

We consider the DD estimates presented in Table 5 as our preferred estimates because they reveal the effect of the release of information about high-quality and low-quality schools on property prices after controlling for school quality. Our approach is consistent with the empirical strategy of Figlio & Lucas (2004) who estimate the effect of information incorporated in state-administered school grades on house prices after controlling for test scores.

4.4 Robustness Checks

We perform several robustness checks to verify our results. First, although suburbs usually have about the same size as school zones, suburb borders are not necessarily consistent with school zone borders. Our analysis focuses on the comparison of *neighboring* treatment and control suburbs within the same postcode area. Although these suburbs often do not share the same border, it is possible that school zones cover parts of a treatment and a control suburb. Unfortunately, we are unable to geo-reference the exact location of suburb and school zone borders. However, we are able to observe suburb and school zone borders within the city of Melbourne. Therefore, we restrict our analysis samples to treatment and control suburbs in Melbourne that are located *almost entirely* within a school zone.[12] The DD estimates obtained from the restricted analysis samples indicate that good news increases property prices by about 7.5 percent. Although the sample size of the restricted sample is relatively small (2,820 observations), the effect is still statistically significant at a 5 percent level (the estimated coefficient is 0.0745 and the standard error is 0.0319). In contrast, we find that bad news did not have a significant effect on property prices in the suburbs of the restricted sample (the estimate obtained from a sample of 2,473 observations is 0.0116 and the standard error is 0.0332). Overall, these results strongly support the main findings of our analysis.

Second, we define treatment and control suburbs based on Year 3 test scores to estimate the effect of the release of school quality information on property prices. The DD estimates similar to those presented in Table 2 indicate that good news regarding Year 3 test scores increases property prices by 3.0 percent. The estimated coefficient is significant at a 5 percent level (coefficient: 0.0296, standard error: 0.0121, number of observations: 12,244). Adding school quality measures to the regression (similar to Table 5) reduces the effect to 2.7 percent but it is still statistically significant at a 5 percent level (coefficient: 0.0267, standard error: 0.0128, number of observations: 12,244). Regardless of the model specification, receiving bad news regarding Year 3 test scores does not have a significant effect on property prices.

Third, we estimate the effect of the release of school quality information by property size. We would expect that prices in the market for one bedroom properties are not affected by school quality information because couples with children should have no interest in buying one bedroom properties. Our estimates confirm that the release

[12] Using only suburbs that are located entirely within a school zone would be too restrictive. A map of suburb and school zone borders is available at `http://melbourneschoolzones.com/`. We use the following suburbs to perform our robustness check: Albert Park, Ardeer, Ashwood, Avondale Heights, Balnarring, Baxter, Beaconsfield, Black Rock, Blackburn South, Box Hill South, Cairnlea, Campbellfield, Caulfield North, Chelsea Heights, Chirnside Park, Croydon Hills, Delahey, Dromana, Elwood, Essendon North, Harkaway, Heidelberg, Hurstbridge, Ivanhoe, Ivanhoe East, Kew East, Kingsbury, Lynbrook, Mernda, Middle Park, Mount Martha, Niddrie, North Melbourne, Park Orchards, Patterson Lakes, Port Melbourne, Princes Hill, Research, Rye, Seabrook, Southbank, Sydenham, Tootgarook, Upper Ferntree Gully, Warranwood, Watsonia, Wattle Glen, Windsor and Wonga Park.

of school quality information has no significant effect on prices of one bedroom properties. Unfortunately, we only observe a relatively small number of one bedroom property sales (169 transactions in the good news sample and 107 transactions in the bad news sample). However, we also find no effect of the release of school quality information on two bedroom properties despite much larger sample sizes (1,857 transactions in the good news sample and 851 transactions in the bad news sample). The effect of good news on prices of three bedroom properties is almost significant at a 10% level (coefficient: 0.0242, standard error: 0.0148 number of observations: 5,229) but our estimates reveal that the overall effect is mainly driven by properties with more than three bedrooms (coefficient: 0.0650, standard error: 0.0156, number of observations: 5,419). These findings suggest that our model captures the effect of the release of school quality information on property prices, which is expected to be larger for large properties.

Finally, we test the validity of the standard errors of our DD model. Bertrand et al. (2004) point out that DD estimates are subject to a possibly severe serial correlation problem. They examine how the DD approach performs if observation units and points in time are chosen at random. Randomising the assignment of observation units should yield a significant "effect" at the 5 percent level roughly 5 percent of the time. Bertrand et al. (2004) use data from the Current Population Survey and two Monte Carlo studies and find dramatically higher rejection rates of the null hypothesis of no effect. When we assign suburbs and time periods randomly, we find that the proportion of type-I errors is 0.056 in our good news sample and 0.050 in our bad news sample, suggesting that the estimates presented in our paper are reliable.

4.5 Results from a Survey of Real Estate Agents

Our findings indicate that the publication of the *My School* website increased property prices by 3.6 percent. It appears likely that this effect was only temporary because the public lost interest in the website within a few weeks. To examine why we observe an effect of good news but no effect of bad news on property prices, we test whether real estate agents, who are more likely to be aware of the school quality in the neighborhood than prospective home buyers, selectively disclose good news to their clients to increase the sales price.[13]

[Figure 7 about here.]

To test this hypothesis, we contacted real estate agents in Victoria through email to conduct a 5 minute web survey.[14] Unfortunately, the response rate of the survey was quite low and we only received complete and valid responses from 56 real estate agents, so discussions of survey point estimates with standard errors are impossible. However, the results obtained from this sample turn out to be quite consistent with the overall message of asymmetric information. Figures 7 and 8 summarize the responses to our two main questions. The responses indicate that most real estate agents are likely to pass on information about high-quality schools (most of the probability mass on 100 percent) to potential buyers, but do not mention low-quality schools (most of the probability mass on 0 percent). These findings provide strong evidence in favor of the hypothesis that real estate agents actively pursue a strategy of selective disclosure of school quality information.

[Figure 8 about here.]

5 Conclusion

Information asymmetry may have considerable effects on the efficient allocation of resources in markets. Situations in which market participants do not possess the same information have been studied extensively by economic theorists. This paper is the first to perform an empirical analysis simultaneously of selective information disclosure on the seller side and unawareness on the buyer side to provide evidence on the channels

[13]Most home sales in Australia are through real estate agents. Only about 1 percent of homes are being sold without an agent (`http://whichrealestateagent.com.au/for-sale-by-owner/`).

[14]Project: "The effect of the release of school quality information on the housing market", University of Melbourne, HREC ID: 1646171.1, Australian National University, Protocol Number: 2016/059.

through which information asymmetry may affect market mechanisms and outcomes. We demonstrate the relevance of these channels by studying the effect of the launch of the Australian Government's *My School* website on housing prices in the state of Victoria. The link between school quality and property prices is well-established in the literature (see Davidoff & Leigh (2008) for evidence on Australia and the citations therein for evidence on the UK and the US). However, very little is known about the dynamic development or consequences of the release of school quality information on property prices.

We use individual home sales data to estimate the effect of the release of information on high-quality or low-quality schools in the neighborhood relative to medium-quality schools. We find that the release of information about high-quality schools ("good news") increases property prices by 3.6 percent ($36,000 on a million dollar home, common in large Australian cities), whereas the release of information about low-quality schools ("bad news") has no significant effect. The effect of good news on property prices remains significant after controlling for direct measures of school quality, indicating that our treatment captures an information effect rather than a school quality effect. Our results are robust with respect to the common trend criterion and a range of placebo and robustness checks.

A survey of real estate agents in Victoria confirms that most real estate agents mention high quality schools in the neighborhood to potential buyers but do not disclose information about low-quality schools. Moreover, the significant effect of selective information disclosure on property prices indicates that many buyers are unaware of the relevance of school quality information because they pay a higher price if they receive good news but they do not respond in a similar, yet opposite manner to bad news. Government interventions requiring, at a minimum, a listing of the names and addresses of all public schools in the catchment area of the property (exactly analogous to the mandatory reporting requirements of easements, flooding or fire-prone areas, zoning restrictions, etc. in the Victorian "Section 32" or vendor's disclosure statement) may be needed to rectify market failure if buyers make uninformed decisions that are socially sub-optimal.

The best case scenario would be a requirement of the vendor to provide complete listing of all public schools in the catchment area *and* their rankings, exactly as displayed by *My School*, included into the vendor's disclosure statement. Many jurisdictions require energy-efficiency ratings to be displayed prominently of household items such as refrigerators or ovens, or automobiles, to make explicit the restrictions or limitations of use of the particular good. For the use of education services (children's schooling) explicitly tied and/or restricted to the purchase of a house in a specific catchment area, this information requirement would be no different.

Figures and Tables

Figure 1: **Screenshot of a Typical Treatment Webpage**

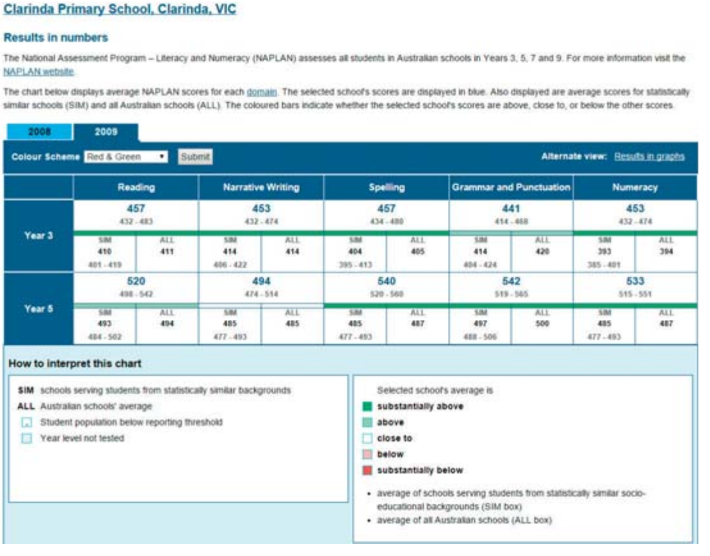
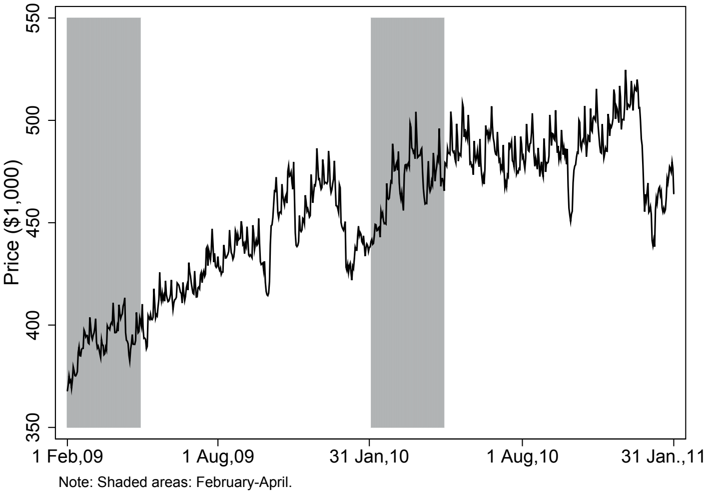


Figure 2: **Mean Property Price (7-day Moving Average), February 2009 – January 2011**



Note: Shaded areas: February-April.

FIGURE 3: **Treatment and Control Suburbs, Victoria and Melbourne**

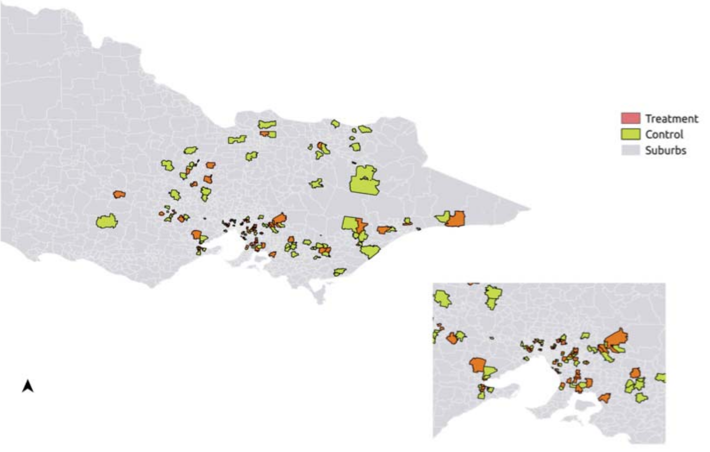


TABLE 1: **Summary Statistics: School Quality and Property Prices**

	Good News Sample			Bad News Sample		
Subject	Treatment	Control	p-value	Treatment	Control	p-value
Reading	508.99	507.32	0.77	484.51	509.39	0.00
	(31.44)	(39.95)		(25.35)	(42.21)	
Narrative Writing	502.21	492.61	0.01	478.33	492.56	0.01
	(24.74)	(24.07)		(28.34)	(25.99)	
Spelling	499.07	487.64	0.01	472.49	488.06	0.01
	(28.32)	(26.71)		(26.18)	(32.40)	
Grammar and Punctuation	519.69	510.76	0.09	492.14	515.07	0.00
	(30.13)	(35.68)		(33.18)	(38.62)	
Numeracy	503.10	495.75	0.12	477.12	501.17	0.00
	(29.51)	(30.48)		(25.83)	(33.34)	
N	67	103	170	43	72	115
Property price, Q1 2009	366.14	347.01	0.00	365.04	360.62	0.56
	(180.62)	(168.56)		(202.59)	(188.92)	
Property price, Q1 2010	468.42	404.62	0.00	455.22	450.98	0.66
	(252.08)	(206.27)		(257.41)	(250.31)	
N	6,913	5,761	12,674	2,005	3,989	5,994

Note: Standard deviations in parentheses. p-values indicate the significance level of the difference in means between treatment and control group.

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

	Good News (Q1 2009 vs. Q1 2010)		Bad News (Q1 2009 vs. Q1 2010)	
	(1)	(2)	(3)	(4)
After	0.1469**	0.1397**	0.1770**	0.1748**
	(0.0080)	(0.0078)	(0.0115)	(0.0115)
DD estimate	0.0462**	0.0430**	0.0166	0.0124
	(0.0135)	(0.0119)	(0.0190)	(0.0183)
Constant	5.7840**	5.7231**	5.7911**	5.7255**
	(0.0049)	(0.0100)	(0.0065)	(0.0143)
Control variables	No	Yes	No	Yes
Adjusted R^2	0.590	0.717	0.577	0.700
F	326.14	138.38	200.16	93.36
N	12,674	12,674	5,994	5,994

Note: The estimates are based on a comparison of neighboring treatment and control suburbs. All models include suburb fixed effects. The results in even columns include a set of control variables. Complete results are presented in Appendix Table A.2. Standard errors (reported in parentheses) were clustered at the suburb level.

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

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

DD Estimates: Good News				DD Estimates: Bad News			
Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
2009 vs. 2010							
0.0430**	0.0077	0.0120	-0.0090	0.0124	0.0024	-0.0050	0.0263
(0.0119)	(0.0096)	(0.0083)	(0.0090)	(0.0183)	(0.0153)	(0.0128)	(0.0160)
[12,674]	[12,686]	[12,367]	[10,004]	[5,994]	[5,852]	[5,734]	[4,827]

Note: The estimates are based on a comparison of neighboring treatment and control suburbs. All models include suburb fixed effects and a set of control variables (see Appendix Table A.1 for a complete list of control variables). Standard errors (reported in parentheses) were clustered at the suburb level. The number of observations is reported in brackets.

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

Figure 4: **Google Trends – Web Search Interest: "my school" Australia, January 2009 – January 2013**

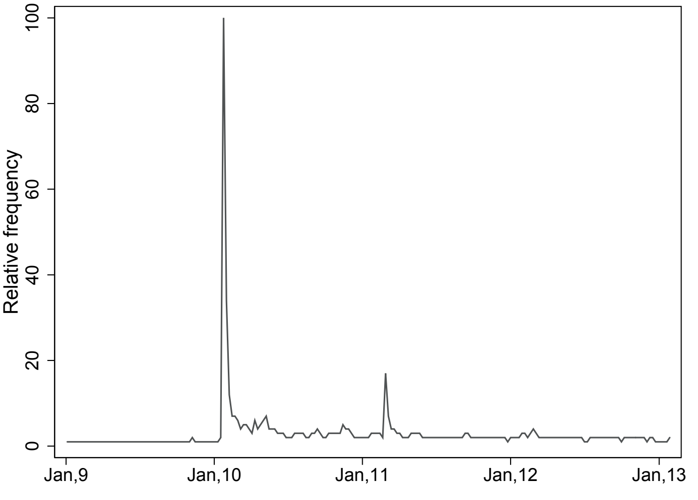


Figure 5: **Test of Common Trend: Good News and Placebo Effects**

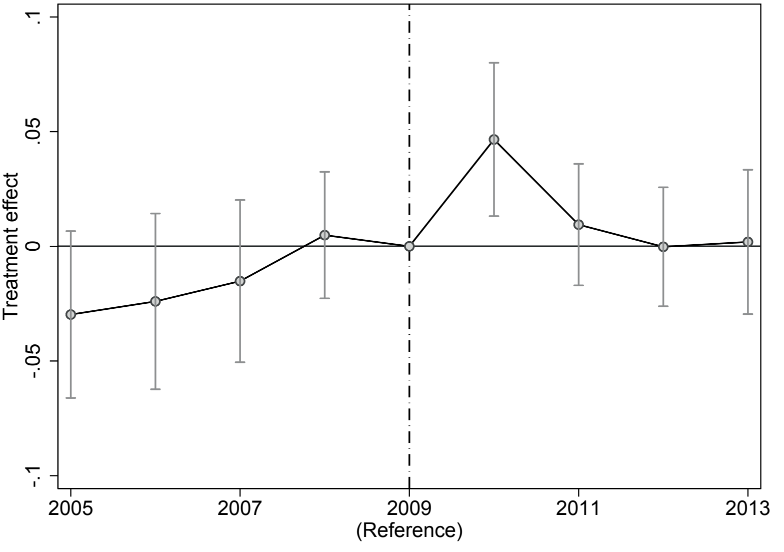


Figure 6: **Test of Common Trend: Bad News and Placebo Effects**

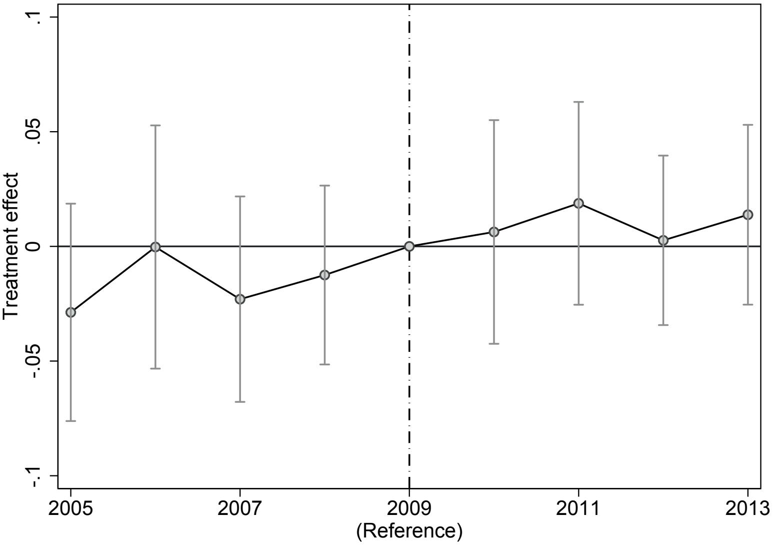


Table 4: **The Effect of School Quality Information on Property Prices and Placebo Effects by Quarter**

	Good News				Bad News			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
2005	-0.0297	-0.0476*	-0.0456	-0.0434	-0.0288	-0.0174	-0.0006	0.0429
	(0.0186)	(0.0219)	(0.0243)	(0.0227)	(0.0242)	(0.0279)	(0.0319)	(0.0304)
2006	-0.0240	-0.0419*	-0.0462*	-0.0064	-0.0003	-0.0204	-0.0140	0.0064
	(0.0196)	(0.0211)	(0.0229)	(0.0204)	(0.0271)	(0.0282)	(0.0299)	(0.0336)
2007	-0.0152	-0.0139	-0.0008	-0.0020	-0.0230	-0.0065	-0.0067	0.0061
	(0.0180)	(0.0184)	(0.0194)	(0.0150)	(0.0228)	(0.0225)	(0.0279)	(0.0265)
2008	0.0049	-0.0070	-0.0187	-0.0082	-0.0125	-0.0060	-0.0043	0.0514*
	(0.0141)	(0.0129)	(0.0140)	(0.0118)	(0.0199)	(0.0196)	(0.0208)	(0.0229)
2010	**0.0466****	0.0087	0.0122	0.0030	**0.0063**	-0.0017	-0.0081	0.0444*
	(**0.0171**)	(0.0138)	(0.0117)	(0.0131)	(**0.0249**)	(0.0212)	(0.0172)	(0.0208)
2011	0.0095	-0.0086	0.0044	-0.0122	0.0188	0.0029	-0.0242	0.0413
	(0.0135)	(0.0126)	(0.0128)	(0.0115)	(0.0226)	(0.0137)	(0.0177)	(0.0238)
2012	-0.0002	-0.0164	-0.0175	-0.0048	0.0026	-0.0279	-0.0013	0.0365
	(0.0132)	(0.0151)	(0.0158)	(0.0133)	(0.0188)	(0.0166)	(0.0190)	(0.0224)
2013	0.0019	0.0084	0.0050	-0.0033	0.0138	0.0170	-0.0121	0.0118
	(0.0161)	(0.0174)	(0.0168)	(0.0173)	(0.0200)	(0.0181)	(0.0366)	(0.0262)
N	52,910	52,661	51,523	47,806	26,138	25,531	25,358	23,772

Note: Reference year: 2009. The estimates are based on a comparison of neighboring treatment and control suburbs. All models include suburb fixed effects and a set of control variables (see Appendix Table A.1 for a complete list of control variables). Standard errors (reported in parentheses) were clustered at the suburb level.

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

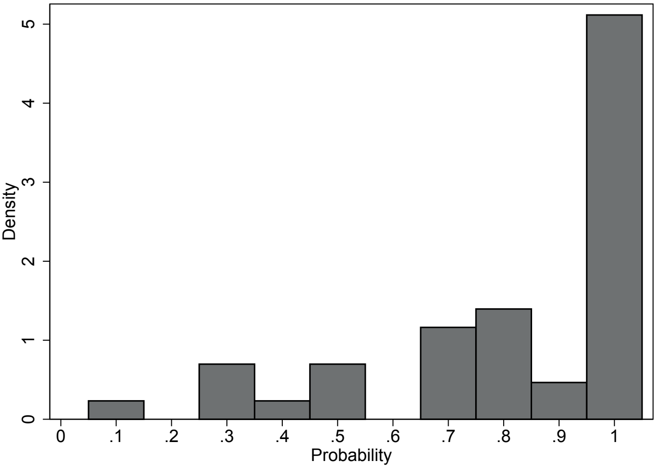
TABLE 5: **The Effect of School Quality Information on Property Prices After Controlling for School Quality**

	Good News (Q1 2009 vs. Q1 2010)		Bad News (Q1 2009 vs. Q1 2010)	
	(1)	(2)	(3)	(4)
After	0.1618**	0.1524**	0.1766**	0.1848**
	(0.0094)	(0.0091)	(0.0127)	(0.0135)
DD estimate	0.0342*	0.0360**	0.0054	0.0049
	(0.0148)	(0.0132)	(0.0187)	(0.0178)
Ln(grammer score)	0.3321	0.2345	0.2568	0.4582
	(0.1849)	(0.1768)	(0.2765)	(0.2668)
Ln(numeracy score)	-0.2265	-0.2745	-0.0643	-0.0752
	(0.2041)	(0.2027)	(0.1587)	(0.1434)
Ln(reading score)	0.1588	0.0708	0.1123	-0.3022
	(0.1921)	(0.1966)	(0.2671)	(0.3098)
Ln(spelling score)	-0.3177	-0.1822	-0.1948	-0.1619
	(0.2673)	(0.2321)	(0.3162)	(0.3023)
Ln(writing score)	0.4577	0.3565	-0.4802*	-0.3302
	(0.2645)	(0.2377)	(0.1930)	(0.1870)
Constant	3.2492*	4.4306**	8.0776**	8.2602**
	(1.4516)	(1.3066)	(1.3419)	(1.5174)
Control variables	No	Yes	No	Yes
Adjusted R^2	0.590	0.717	0.577	0.700
F	138.48	138.02	69.32	91.35
N	12,674	12,674	5,994	5,994

Note: The estimates are based on a comparison of neighboring treatment and control suburbs. All models include suburb fixed effects. The results in even columns include a set of control variables. Complete results are presented in Appendix Table A.2. Standard errors (reported in parentheses) were clustered at the suburb level.

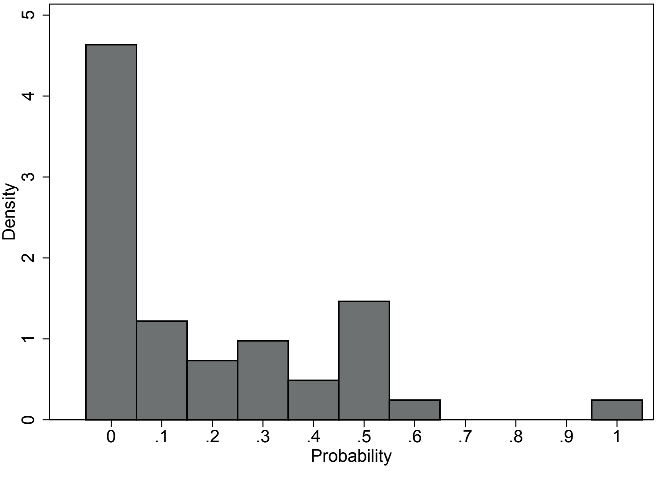
* p <0.05, ** p <0.01.

Figure 7: **Survey of Real Estate Agents: Disclosure of Good News**



Survey question: "What is the probability that you would mention school quality to potential buyers, if you knew that schools in the neighbourhood are GOOD?"

Figure 8: **Survey of Real Estate Agents: Disclosure of Bad News**



Survey question: "What is the probability that you would mention school quality to potential buyers, if you knew that schools in the neighbourhood are BAD?"

References

Akerlof, G. A. (1970). The Market for “Lemons”: Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, *84*(3), 488–500.

Auster, S. (2013). Asymmetric Awareness and Moral Hazard. *Games and Economic Behavior*, *82*, 503–521.

Australian Bureau of Statistics (2011). Schools, Australia, 2010. Annual Publication, Commonwealth of Australia, Canberra.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How Much Should We Trust Differences-in-Differences Estimates? *The Quarterly Journal of Economics*, *119*(1), 249–275.

Carrillo, P., Cellini, S. R., & Green, R. K. (2013). School Quality and Information Disclosure: Evidence from the Housing Market. *Economic Inquiry*, *51*(3), 1809–1828.

Davidoff, I., & Leigh, A. (2008). How Much do Public Schools Really Cost? Estimating the Relationship between House Prices and School Quality. *The Economic Record*, *84*(265), 193–206.

DellaVigna, S., & Malmendier, U. (2004). Contract Design and Self-Control: Theory and Evidence. *The Quarterly Journal of Economics*, *119*(2), 353–402.

Eliaz, K., & Spiegler, R. (2006). Contracting with Diversely Naive Agents. *The Review of Economic Studies*, *73*(3), 689–714.

Eliaz, K., & Spiegler, R. (2011). Consideration Sets and Competitive Marketing. *The Review of Economic Studies*, *78*(1), 235–262.

Figlio, D. N., & Lucas, M. E. (2004). What’s in a Grade? School Report Cards and the Housing Market. *The American Economic Review*, *94*(3), 591–604.

Filiz-Ozbay, E. (2012). Incorporating Unawareness into Contract Theory. *Games and Economic Behavior*, *76*(1), 181–194.

Gabaix, X., & Laibson, D. (2006). Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets. *The Quarterly Journal of Economics*, *121*(2), 505–540.

Grossman, S. J. (1981). The Informational Role of Warranties and Private Disclosure About Product Quality. *The Journal of Law & Economics*, *24*(3), 461–483.

Imberman, S. A., & Lovenheim, M. F. (2016). Does the Market Value Value-Added? Evidence from Housing Prices After a Public Release of School and Teacher Value-Added. *Journal of Urban Economics*, *91*, 104–121.

Li, S., Peitz, M., & Zhao, X. (2016). Information Disclosure and Consumer Awareness. *Journal of Economic Behavior & Organization*, *128*, 209–230.

Milgrom, P. (2008). What the Deller Won't Yell You: Persuasion and Disclosure in Markets. *The Journal of Economic Perspectives*, *22*(2), 115–131.

Milgrom, P., & Roberts, J. (1986). Relying on the Information of Interested Parties. *The RAND Journal of Economics*, *17*(1), 18–32.

Milgrom, P. R. (1981). Good News and Bad News: Representation Theorems and Applications. *The Bell Journal of Economics*, *12*(2), 380–391.

Mullainathan, S., Schwartzstein, J., & Shleifer, A. (2008). Coarse Thinking and Persuasion. *The Quarterly Journal of Economics*, *123*(2), 577–619.

Shapiro, J. M. (2006). A 'Memory-Jamming' Theory of Advertising. *Available at SSRN 903474*.

Spiegler, R. (2006). The Market for Quacks. *The Review of Economic Studies*, *73*(4), 1113–1131.

Zhou, J. (2008). Advertising, Misperceived Preferences, and Product Design. *Mimeo: NYU Stern School of Business*.

Appendix

Table A.1: **Property Characteristics, Good News Sample**

	2009			2010		
Variable	Treatment	Control	p-value	Treatment	Control	p-value
Property size (sqm)	994	1,494	0.00	1,021	1,853	0.00
	(4,382)	(6,171)		(4,079)	(9,184)	
Bedrooms	3.047	3.073	0.28	3.071	3.120	0.04
	(0.892)	(0.781)		(0.828)	(0.831)	
Bathrooms	1.531	1.531	0.99	1.547	1.548	0.95
	(0.617)	(0.600)		(0.629)	(0.594)	
Parking	1.804	1.942	0.00	1.810	1.924	0.00
	(0.889)	(1.035)		(0.837)	(1.009)	
House	0.708	0.759	0.00	0.724	0.796	0.00
	(0.455)	(0.428)		(0.447)	(0.403)	
Terrace	0.006	0.004	0.11	0.010	0.005	0.02
	(0.080)	(0.059)		(0.099)	(0.069)	
Townhouse	0.050	0.041	0.08	0.055	0.037	0.00
	(0.218)	(0.197)		(0.228)	(0.189)	
Unit	0.233	0.194	0.00	0.209	0.161	0.00
	(0.423)	(0.396)		(0.407)	(0.367)	
Air conditioning	0.218	0.211	0.49	0.215	0.208	0.52
	(0.413)	(0.408)		(0.411)	(0.406)	
Alarm	0.063	0.059	0.58	0.067	0.063	0.49
	(0.242)	(0.236)		(0.251)	(0.243)	
Balcony	0.045	0.036	0.09	0.045	0.035	0.04
	(0.207)	(0.187)		(0.208)	(0.185)	
Barbeque	0.035	0.039	0.47	0.043	0.038	0.27
	(0.184)	(0.192)		(0.203)	(0.190)	
Courtyard	0.094	0.076	0.01	0.093	0.063	0.00
	(0.292)	(0.265)		(0.290)	(0.244)	
Ensuite	0.261	0.261	0.97	0.259	0.271	0.29
	(0.439)	(0.439)		(0.438)	(0.444)	
Family room	0.031	0.030	0.79	0.028	0.039	0.01
	(0.174)	(0.171)		(0.164)	(0.193)	
Fireplace	0.009	0.012	0.26	0.030	0.036	0.18
	(0.097)	(0.111)		(0.171)	(0.187)	
Garage	0.128	0.128	0.99	0.131	0.129	0.78
	(0.335)	(0.334)		(0.338)	(0.335)	
Heating	0.406	0.375	0.01	0.413	0.394	0.13
	(0.491)	(0.484)		(0.492)	(0.489)	

Continued on next page...

Table A.1 (Continued)

	2009			2010		
Variable	Treatment	Control	p-value	Treatment	Control	p-value
Internal laundry	0.013	0.014	0.68	0.015	0.017	0.35
	(0.114)	(0.120)		(0.120)	(0.131)	
Locked garage	0.193	0.205	0.25	0.142	0.132	0.26
	(0.395)	(0.404)		(0.349)	(0.339)	
Polished timber floor	0.102	0.108	0.47	0.101	0.091	0.19
	(0.303)	(0.310)		(0.302)	(0.288)	
Pool	0.005	0.004	0.55	0.005	0.010	0.04
	(0.073)	(0.065)		(0.073)	(0.099)	
Rumpus room	0.071	0.071	0.95	0.083	0.074	0.15
	(0.257)	(0.258)		(0.276)	(0.261)	
Separate dining	0.043	0.034	0.07	0.036	0.035	0.94
	(0.203)	(0.181)		(0.186)	(0.185)	
Spa	0.367	0.343	0.06	0.175	0.179	0.63
	(0.482)	(0.475)		(0.380)	(0.384)	
Study	0.172	0.191	0.05	0.186	0.184	0.86
	(0.377)	(0.393)		(0.389)	(0.388)	
Sun room	0.014	0.014	0.98	0.019	0.015	0.26
	(0.119)	(0.120)		(0.137)	(0.123)	
Walk-in wardrobe	0.147	0.147	0.96	0.127	0.143	0.07
	(0.354)	(0.355)		(0.333)	(0.350)	
N	3,396	2,830	6,226	3,517	2,931	6,448

Note: Standard deviations in parentheses. p-values indicate the significance level of the difference in means between treatment and control group.

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

	Q1 2009 vs. Q1 2010			
	Good News		Bad News	
	(1)	(2)	(3)	(4)
After	0.1397**	0.1524**	0.1748**	0.1848**
	(0.0078)	(0.0091)	(0.0115)	(0.0135)
DD estimate	0.0430**	0.0360**	0.0124	0.0049
	(0.0119)	(0.0132)	(0.0183)	(0.0178)
Ln(grammer score)		0.2345		0.4582
		(0.1768)		(0.2668)
Ln(numeracy score)		-0.2745		-0.0752
		(0.2027)		(0.1434)
Ln(reading score)		0.0708		-0.3022
		(0.1966)		(0.3098)
Ln(spelling score)		-0.1822		-0.1619
		(0.2321)		(0.3023)
Ln(writing score)		0.3565		-0.3302
		(0.2377)		(0.1870)
Size $\leq$ 200sqm	-0.0042	-0.0042	0.0136	0.0138
	(0.0148)	(0.0148)	(0.0230)	(0.0229)
Size $>$200sqm & $\leq$ 400sqm	0.0582**	0.0579**	0.0769**	0.0774**
	(0.0129)	(0.0130)	(0.0210)	(0.0211)
Size $>$400sqm & $\leq$ 600sqm	-0.0083	-0.0087	-0.0273*	-0.0273*
	(0.0085)	(0.0086)	(0.0132)	(0.0132)
Size $>$900sqm	0.1099**	0.1099**	0.0538**	0.0548**
	(0.0125)	(0.0125)	(0.0189)	(0.0189)
Size missing or implausible	-0.0325	-0.0341	-0.0786	-0.0773
	(0.0757)	(0.0755)	(0.1140)	(0.1146)
1-2 bedroom	-0.1251**	-0.1252**	-0.1470**	-0.1466**
	(0.0099)	(0.0098)	(0.0156)	(0.0157)
5+ bedroom	0.1356**	0.1356**	0.1832**	0.1837**
	(0.0139)	(0.0139)	(0.0277)	(0.0278)
Missing bedroom	-0.0582**	-0.0579**	-0.0037	-0.0039
	(0.0117)	(0.0117)	(0.0199)	(0.0199)
2+ bathroom	0.1553**	0.1554**	0.1802**	0.1802**
	(0.0111)	(0.0111)	(0.0147)	(0.0147)
Missing bathroom	0.0896**	0.0896**	0.0524*	0.0531*
	(0.0161)	(0.0161)	(0.0222)	(0.0223)

Continued on next page...

Table A.2 (Continued)

	Q1 2009 vs. Q1 2010			
	Good News		Bad News	
	(1)	(2)	(3)	(4)
3+ parking	0.0541**	0.0540**	0.0945**	0.0939**
	(0.0091)	(0.0091)	(0.0139)	(0.0140)
Missing/no parking	-0.0332**	-0.0332**	-0.0187	-0.0183
	(0.0100)	(0.0100)	(0.0140)	(0.0140)
Terrace	-0.0529	-0.0522	0.0023	-0.0001
	(0.0365)	(0.0364)	(0.0625)	(0.0623)
Townhouse	-0.1071**	-0.1073**	-0.1135**	-0.1135**
	(0.0161)	(0.0162)	(0.0319)	(0.0318)
Unit	-0.1850**	-0.1849**	-0.2033**	-0.2039**
	(0.0149)	(0.0150)	(0.0222)	(0.0222)
Air conditioning	-0.0117*	-0.0118*	-0.0128	-0.0131
	(0.0052)	(0.0052)	(0.0082)	(0.0082)
Alarm	0.0463**	0.0466**	0.0533**	0.0528**
	(0.0098)	(0.0099)	(0.0140)	(0.0140)
Balcony	0.0344*	0.0339*	0.0390	0.0395
	(0.0139)	(0.0139)	(0.0245)	(0.0245)
Barbeque	-0.0197	-0.0202	0.0003	0.0015
	(0.0104)	(0.0104)	(0.0168)	(0.0167)
Courtyard	-0.0036	-0.0037	0.0301*	0.0310*
	(0.0108)	(0.0108)	(0.0125)	(0.0126)
Ensuite	0.0131	0.0131	-0.0163	-0.0165
	(0.0082)	(0.0082)	(0.0119)	(0.0118)
Family room	-0.0020	-0.0012	-0.0092	-0.0095
	(0.0122)	(0.0121)	(0.0228)	(0.0227)
Fireplace	0.0928**	0.0930**	0.1036**	0.1041**
	(0.0202)	(0.0202)	(0.0235)	(0.0234)
Garage	0.0459**	0.0455**	0.0267**	0.0277**
	(0.0072)	(0.0071)	(0.0096)	(0.0097)
Heating	-0.0045	-0.0047	-0.0002	-0.0001
	(0.0059)	(0.0059)	(0.0083)	(0.0083)
Internal laundry	-0.0136	-0.0124	-0.0285	-0.0317
	(0.0174)	(0.0175)	(0.0224)	(0.0226)
Locked garage	0.0201**	0.0205**	0.0089	0.0093
	(0.0069)	(0.0070)	(0.0099)	(0.0099)
Polished timber floor	0.0139*	0.0140*	0.0084	0.0083
	(0.0062)	(0.0062)	(0.0108)	(0.0108)

Continued on next page...

Table A.2 (Continued)

	Q1 2009 vs. Q1 2010			
	Good News		Bad News	
	(1)	(2)	(3)	(4)
Pool	0.0386	0.0384	0.0590	0.0619
	(0.0426)	(0.0426)	(0.0327)	(0.0326)
Rumpus room	0.0761**	0.0755**	0.0441**	0.0446**
	(0.0082)	(0.0082)	(0.0115)	(0.0115)
Separate dining	-0.0007	-0.0013	0.0214	0.0207
	(0.0095)	(0.0095)	(0.0183)	(0.0185)
Spa	0.0033	0.0038	0.0114	0.0116
	(0.0062)	(0.0062)	(0.0096)	(0.0096)
Study	0.0753**	0.0754**	0.0777**	0.0778**
	(0.0065)	(0.0065)	(0.0097)	(0.0097)
Sun room	-0.0032	-0.0032	-0.0023	-0.0025
	(0.0165)	(0.0165)	(0.0269)	(0.0268)
Walk-in wardrobe	0.0229**	0.0230**	0.0184	0.0191
	(0.0076)	(0.0076)	(0.0114)	(0.0114)
Constant	5.7231**	4.4306**	5.7255**	8.2602**
	(0.0100)	(1.3066)	(0.0143)	(1.5174)
N	12,674	12,674	5,994	5,994

Note: The estimates are based on a comparison of neighboring treatment and control suburbs. All models include suburb fixed effects. Reference groups were chosen based on sample size; the largest subgroups within each category are properties with sizes between >600sqm and ≤900sqm, 3-4 bedrooms, 1 bathroom, and 1-2 parking. Standard errors (in parentheses) were clustered at the suburb level.

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