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Consumer Mistakes and Advertising: The Case of Mortgage Refinancing

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Abstract

Does advertising help consumers to find the products they need or push them to buy products they don't need? In this paper, we study the effects of advertising on consumer mistakes and quantify the resulting effect on consumer welfare in the market for mortgage refinancing. Mortgage borrowers frequently make costly refinancing mistakes by either refinancing when they should wait, or by waiting when they should refinance. We assemble a novel data set that combines a borrower's exposure to direct mail refinance advertising and their subsequent refinancing decisions. Even though on average borrowers would lose approximately $500 by refinancing, the average monthly exposure of 0.23 refinancing advertisements reduces the expected net present value of mortgage payments on average by $13, because borrowers who should refinance are targeted by advertisers and more responsive to advertising. A counterfactual advertising policy that redirects all advertising to borrowers who should refinance would increase the gain in borrower welfare to $45.

JEL Codes: M37, G21, D14

Keywords: Advertising, Mistakes, Mortgage, Refinancing

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1 Introduction

Consumers are susceptible to making mistakes, and firms engage in various activities that can either encourage or prevent consumer mistakes, which has important policy implications. On the one hand, firms exploit the behavioral biases of consumers to sell them products they don't need or to sell them overpriced products. Akerlof and Shiller (2015) argue that such activities are a central part of free market economies. Examples include shrouding (Gabaix and Laibson (2006)), credit contracts with back-loaded repayment schedules (Heidhues and Koszegi (2010)), or conditioning offers on consumer naivete (Heidhues and Koszegi (2016)). Policies that restrict or regulate such activities, for example the CARD Act or the Qualified Mortgage Rule, can therefore be beneficial for consumers who are susceptible to making mistakes. On the other hand, firms have an incentive to help consumers if they fail to buy products they do need, for example by providing information or by educating them about the benefits of a product. Hence, policies that restrict such activities can be harmful for consumers who are susceptible to making mistakes. Instead, policy makers should facilitate such activities.

Advertising is an important firm activity that can either encourage or prevent consumer mistakes. Some view advertising as an attempt to sell consumers products they don't need and others view it as helping consumers to find the products they do need. In the theoretical advertising literature the former view is loosely associated with models of deceptive advertising and models of persuasive advertising, whereas the latter view is associated with models of informative advertising.[1] In many markets advertising has both roles at the same time, so the net effect of advertising on consumer welfare through mistakes is unclear.

In this paper, we estimate the effect of advertising on consumer mistakes and quantify the resulting net effect on consumer welfare in the market for mortgage refinancing. In our theoretical framework the effect of advertising on consumer welfare through its impact on consumer mistakes depends on three determinants. First, the composition of consumers, which determines how much the average consumer gains or loses from buying the product. Second, targeting and intensity of advertising, which determines whether and how much advertisers target those consumers who stand to gain the most from buying the product. Third, differential responsiveness, i.e., whether consumers who stand to gain more from buying the product are more responsive to advertising. We quantify the importance of these three factors empirically in the market for mortgage advertising and investigate the potential impact of improved targeting in a counterfactual experiment.

The effect of advertising on consumer mistakes and the resulting net effect on consumer welfare has not been studied empirically before. There are two important reasons for the scarcity of

[1] Ozga (1960), Stigler (1961a), Telser (1964), Nelson (1970, 1974) and Grossman and Shapiro (1984) are references on informative advertising. Braithwaite (1928), Robinson (1933) or Kaldor (1950) are early references on persuasive advertising and Glaeser and Ujhelyi (2010) is a recent reference on deceptive advertising.

empirical work. First, for many products advertising is likely to affect not only the probability that a consumer buys a product but also the utility the consumer gets from consuming the product. For example, because advertising increases the prestige associated with the product. Second, even in markets in which advertising affects only the probability of purchase but not the consumption utility, there is usually no objective measure of consumption utility because it depends on unobserved tastes. Therefore consumer mistakes cannot be detected and quantified in choice data, because many choices can be rationalized by unobserved tastes.

We argue that the refi setting allows us to detect and quantify mistakes in choice data and therefore serves as a laboratory to study the effect of advertising on consumer mistakes empirically.[2] First, advertising is unlikely to affect the consumption utility a borrower gets from refinancing because refi loans are not consumed there are no prestige effects in refi advertising. Second, the net present value of mortgage payments is an objective measure of the benefit of refinancing. Therefore refi mistakes can be detected and quantified in choice data.

This has been recognized in the growing literature on refi mistakes (Agarwal, Rosen, and Yao (2015), Keys, Pope, and Pope (2016), Andersen, Campbell, Nielsen, and Ramadorai (2017)).[3] Borrowers frequently make costly refinancing mistakes. If a borrower refinances her fixed rate mortgage, she can take advantage of a lower mortgage rate, but she must pay a refinancing cost. If the market mortgage rate falls sufficiently far below the borrower's mortgage rate, it reaches a trigger point where it becomes optimal to exercise the refinancing option. Some borrowers refinance their mortgage prematurely, before the optimal trigger rate is reached. Other inattentive borrowers refinance too late or not at all. Such refinance mistakes can be very costly because for most households their mortgage is the largest liability.[4]

Refi advertising can help inattentive borrowers who should refinance but fail to take advantage of lower interest rates by informing them. However, refi ads can also be deceptive. Lenders commonly advertise the projected reduction in monthly mortgage payments without pointing out that this reduction is partly achieved through an extension of the loan term, rather than through a reduction of the interest rate. Such ads have the potential to convince borrowers who should wait to refinance prematurely.

[2]Following the terminology in the literature on "refinancing mistakes", we refer to decisions as "mistakes" whenever an alternative decision yields a higher expected payoff, if we condition on all relevant information - whether this information was available to the decision maker or not. Such decisions are not always called mistakes. For example, such decisions can be optimal in models of rational inattention or models of costly reasoning (e.g. Andersen, Campbell, Nielsen, and Ramadorai (2017)). However, we believe that such reinterpretations of "mistakes" do not need to change the interpretation of our results. A rationally inattentive borrower for example, who fails to take advantage of lower interest rates, would still benefit from advertising that draws her attention. A rationally inattentive borrower who should not refinance might be harmed by advertising that draws her attention even if she does not refinance, however.

[3]See also Green and LaCour-Little (1999), Schwartz (2006) and Campbell (2006).

[4]For example Keys, Pope, and Pope (2016) estimate that the median loss among households who fail to refinance when the interest rate reaches the optimal trigger rate is $11,500.

The ideal data set to study the effect of refi advertising on borrower mistakes should provide information on advertising exposure of different mortgage borrowers and their subsequent refinancing decisions. However, such a data set is not readily available. With data on advertising through mass media such as TV, newspaper and radio, it is difficult to observe whether advertising is seen by mortgage borrowers with different loan characteristics because the aggregate nature of the mass advertising.[5] Although Mintel Comperemedia (henceforth "Mintel") collects information on direct mail advertisements and characteristics of their recipients, the data set does not provide information about the recipients' refinancing decisions. One common limitation of previous studies using the Mintel data is that the choice of the consumers who received direct-mail advertising could not be observed.[6]

We overcome the data limitation by assembling a novel borrower-level data set that combines a borrower's exposure to direct mail refinance advertising and their subsequent refinancing decisions. We merge the direct mail data from Mintel with borrower-level mortgage data from Credit Risk Insight Servicing McDash (CRISM), based on three common variables: a borrower's zipcode, age and exact outstanding mortgage balance in a given month.[7] Unlike more common loan-level data, the CRISM data allows us to observe when borrowers refinance their mortgage. Moreover, CRISM tracks important borrower characteristics such as the FICO score over time so we can focus on borrowers who are likely to qualify for a refi loan.[8] Another important advantage of the data is that it allows us to capture the spillover effects of advertising, i.e. we estimate the effect of refi advertising on the overall probability of refinancing rather than only on the probability of refinancing with the advertising lender.[9]

We begin by formally laying out how advertising can affect borrower welfare in our framework, which imposes two important restrictions. First, we assume that refi advertising only affects the probability that the borrower refinances, but not the utility the borrower enjoys from refinancing. Second, we only consider the direct effects of advertising on the purchase probability, not equilibrium effects (e.g. on prices). In this framework, advertising affects borrower welfare only through its effect on the probability that borrowers make refi mistakes - either by refinancing prematurely or by failing to refinance when they should. We show that under these assumptions, the net effect of advertising on borrower welfare depends on three factors. First, differential responsiveness, i.e. whether borrowers who should refinance are more responsive to advertising, than those who

[5] The mass advertising data are usually available from Kantar Media.

[6] Recent papers using the Mintel data include Han, Keys, and Li (2013), Ru and Schoar (2016), and Grodzicki (2015).

[7] CRISM combines credit bureau data from Equifax matched to the loan-level McDash loan servicing data (formerly Lender Processing Service).

[8] Andersen, Campbell, Nielsen, and Ramadorai (2017) point out that studying refi mistakes with US data can be problematic because the borrower characteristics are typically only observed at the time of origination.

[9] See Sinkinson and Starc (2015) and Shapiro (2016) for advertising spillovers.

shouldn't. Second, targeting and intensity of advertising, which determines whether and how much advertisers target borrowers who should refinance. Third, borrower composition, i.e. how many borrowers should refinance and how many should wait, and how much can they gain or lose if they decide to refinance.

To study differential responsiveness, we estimate the borrower's refi policy function. We divide the borrowers into those who should refinance and those who should wait following the literature on refi mistakes. To determine whether a borrower should refinance we follow the literature on refi mistakes and use the optimal refinancing policy proposed by Agarwal, Driscoll, and Laibson (2013). We find that advertising increases the refi probability for the small group of borrowers who should refinance by approximately 4 percentage points or roughly 25%, over the three quarters after receiving an refi ad. However, advertising has no significant effect on larger group of borrowers who should wait. These estimates suggest that refi advertising helps borrowers who should refinance without hurting borrowers who should wait.

Endogeneity is a common concern in empirical studies of advertising. If advertisers use unobservable consumer characteristics to target consumers who are inherently more likely to buy the product regardless of advertising exposure, then the researcher would overstate the average effect of advertising. It is less clear if targeting based on unobservables would affect estimates of differential responsiveness and if yes, in which direction. In general we do not regard targeting based on unobservables as a major concern in our setting, because we observe many borrower characteristics, including information from a credit bureau, that is not observed by most advertisers.[10] It can however be an important concern for those advertisers that have ongoing relationships with the borrower through other lines of business (e.g. checking accounts), and therefore observe borrower characteristics that we do not observe. We address this concern by exploiting the fact that about one half of the advertisers are specialized mortgage firms such as Quicken Loans, which typically have no ongoing relationships with the borrowers, other than through the mortgage. We use advertising sent by specialized mortgage firms as an instrument for overall advertising, and our IV estimates are similar to the baseline estimates that treat advertising as exogenous.

To quantify the effect of refi advertising on borrower welfare, we measure borrower welfare as the expected net present value of mortgage payments. Even though the borrower composition is such that the average borrower would lose approximately \$500 from refinancing, the average monthly exposure of 0.23 refi ads reduces the net present value of mortgage payments by \$9-\$13. This is due to differential responsiveness and targeting, i.e. borrowers who should refinance are more responsive to advertising and more likely to receive advertising. Without differential

[10] It is worth noting that our estimates of the average effect of advertising are relatively small and in some specifications not statistically significant at conventional levels. This suggests that the endogeneity concern due to targeting based on unobservables might be limited.

responsiveness, i.e. if all borrowers were equally responsive to advertising, the benefit would decrease to \$0-\$0.5. Without targeting, i.e. if all borrowers would receive the average amount of refi advertising, the benefit of advertising would decrease to \$4-\$11. The relatively small decrease in the benefit of advertising if targeting is "turned off" suggests that the observed advertising policy is only slightly better than untargeted advertising.

This motivates our counterfactual experiment, in which we investigate the potential benefits of improved targeting. An advertising policy that redirects all advertising to those borrowers who should refinance, leaving the total amount of advertising (advertising intensity) unchanged, would increase the benefit of advertising from \$9-\$13 to \$45-\$50. Because borrowers who should refinance are more responsive to advertising than those who should wait, the responsiveness of the average ad recipient would be about 5 times larger in this counterfactual than under the observed advertising policy. Therefore, advertisers would likely also be better off with improved targeting.

What are the policy implications of these findings? First, even though most borrowers should not refinance, an advertising ban for refi loans would harm borrowers overall. Second, policies that allow advertisers to better target borrowers who should refinance could benefit borrowers and advertisers. However, the benefits of such a policy would have to be weighed against the privacy concern of borrowers. Conversely, our finding suggests that policies that are aimed at protecting the privacy of consumers can make consumers worse off if they they make targeting more difficult.

Literature This paper contributes to the literature on firm activities and consumer mistakes. Brown, Hossain, and Morgan (2010) and Chetty, Looney, and Kroft (2009) provide empirical evidence from field experiments that consumers are inattentive to hidden or non salient attributes of products. Other papers have studied how the susceptibility of consumers to make mistakes affects firm incentives and activities and documented that firms target unsophisticated consumers (e.g. Ru and Schoar (2016) and Seim, Vitorino, and Muir (2016)). This paper makes three contributions to this literature. First, we have an "objective" measure of consumer welfare and can therefore quantify the welfare impact of the activity. Second, we observe which consumers respond to the firm activity and can therefore study differential responsiveness. Third, we highlight that firm activities can sometimes help consumers to prevent mistakes rather than encourage them.

We also contribute to the empirical literature on advertising. There are very few papers trying to estimate the effect of advertising on consumer welfare.[11] One strand of the empirical advertising literature tries to distinguish different models of advertising that posit different mechanisms by which advertising affects consumer decision making (e.g. Ackerberg (2001), Ackerberg (2003), Ching and Ishihara (2012) and Honka, Hortaçsu, and Vitorino (2016)). Different mechanisms

[11] Dubois, Griffith, and O'Connell (2016) is an exception. They rely on a structural model and quantify the effect of advertising under alternative assumptions about the mechanism by which advertising affects decision making.

by which advertising affects decision making are loosely related to the effect of advertising on consumer welfare. For example, it is natural to argue that advertising has a positive effect on consumer welfare if it is informative and a negative effect if it is deceptive.[12] In this paper we measure directly how much borrowers would benefit from refinancing, which allows us to estimate the effect of advertising on borrower welfare without even specifying possible mechanisms by which advertising affects decision making.[13]

This paper contributes to the ongoing debate about targeted advertising. Some researchers have studied whether advertisers target consumers who are vulnerable.[14] For example, Ru and Schoar (2016) find that credit card companies target less sophisticated households with direct-mail offers with teaser rates and back-loaded fees. Our contribution is that the refi setting allows us to study whether advertisers target consumers who should buy the product. Unlike targeting of vulnerable consumers such targeting can increase consumer surplus. However, the benefits of targeting must still be weighed against the privacy concerns of consumers (see Goldfarb and Tucker (2011), Johnson (2013) and the survey by Tucker (2012)). Hence, policy makers should restrict the access of advertisers to information about the vulnerability of consumers, but there is a trade-off if similar restrictions apply to information about which consumers stand to gain from advertising.

Recently, a literature on advertising in markets for consumer financial products has emerged.[15] The most closely related papers are Johnson, Meier, and Toubia (2015) and Gurun, Matvos, and Seru (2016), which study advertising in the mortgage market. Johnson, Meier, and Toubia (2015) present survey evidence that the failure of households to take up pre-approved HARP (Home Affordable Refinancing Program) offers can be explained with suspicion towards the motives of the financial institution. Gurun, Matvos, and Seru (2016) find that subprime lenders that advertise more are more expensive. There are several important differences between Gurun, Matvos, and Seru (2016) and our paper. First, we focus on prime borrowers who already have a mortgage and might want to refinance. Second, we focus on the decision whether to refinance, not on the choice of the lender. Lastly, our data allows us to study the responsiveness of borrowers to advertising.

The remainder of this paper is structured as follows. Section 2 explains how how advertising can affect borrower welfare in our framework, how we measure borrower welfare empirically and how our theoretical framework relates to different models of advertising in the literature. Section 3 describes the data and presents summary statistics. In Section 4 we estimate the refi policy function and find that borrowers who should refinance are more responsive to advertising than

[12] However, this is not necessarily the case as we discuss in section 2.3.

[13] Notice however that our framework rules out some mechanisms by which advertising affects decision making. For details see the discussion of the theoretical advertising literature at the end of Section 2.

[14] See Heidhues and Koszegi (2016) for a theoretical contribution.

[15] See Hastings, Hortacsu, and Syverson (2013) for advertising of privatized pension plans, Aizawa and Kim (2015) advertising in health insurance, Grodzicki (2015) for credit card advertising, and Honka, Hortaçsu, and Vitorino (2016) for advertising of bank accounts.

borrowers who should wait. Section 5 quantifies the effect of advertising on borrower welfare, shows how improved targeting could increase the benefit from advertising, and discuss possible policy implications. Section 6 concludes.

2 Advertising and Consumer Welfare

2.1 Theoretical Framework

Consumer i decides whether to buy a product or to wait and potentially buy it later. Let x be a vector of relevant state variables. If the consumer buys the product she will experience utility $U_{buy}(x)$ and if she waits $U_{wait}(x)$. U_{buy} and U_{wait} are unknown to the consumer because she does not know all the benefits the product might provide or drawbacks it might have. For some products U_{buy} and U_{wait} are realized over a long period of time and can depend on future states of the world. For example, if the consumer buys a refi loan U_{buy} and U_{wait} depend on the realization of future mortgage rates.

The consumer's expected utility from buying the product is $\widetilde{u}_{buy,i}(x) = E_i\left[U_{buy}|x\right]$. Similarly, $\widetilde{u}_{wait,i}(x) = E_i\left[U_{wait}|x\right]$. The expectation operator E_i takes expectations using the consumer's beliefs $\widetilde{g}_i$, about the benefits and drawbacks of the product. Consumer i chooses to buy the product if $\widetilde{u}_{buy,i}(x) \geq \widetilde{u}_{wait,i}(x)$ and waits otherwise.

An important restriction embedded in this formulation is that after conditioning on x, differences in decisions across consumers are only due to differences in beliefs $\widetilde{g}_i$ not due to differences in preferences preferences $U_{buy}(x)$ and $U_{wait}(x)$. Whether this is a plausible assumption depends whether x is large enough. Later, we will discuss the plausibility of this assumption in our mortgage setting.

The probability that a randomly drawn consumer with state vector x buys the product is $\sigma(x) = \Pr\left[\widetilde{u}_{buy,i}(x) \geq \widetilde{u}_{wait,i}(x)|x\right]$.

Mistakes We allow the consumer to make mistakes. Mistakes are due to incorrect beliefs $\widetilde{g}_i$ about the benefits or drawbacks of the product. Let $u_{buy}(x) = E\left[U_{buy}|x\right]$ and $u_{wait}(x) = E\left[U_{wait}|x\right]$ be the "objective" expected utilities associated with buying and waiting, where the expectations are taken using the "objective" belief g, which does not vary over consumers. Let σ^* be the optimal decision rule, which is defined as $\sigma^*(x) = 1$ if $u_{buy}(x) \geq u_{wait}(x)$ and $\sigma^*(x) = 0$, otherwise.

There are many reasons why consumer beliefs $\widetilde{g}_i$ might differ from g, not all of which are commonly referred to as mistakes. For example, the beliefs can differ due to information frictions or rational inattention. In this paper we say that consumers make mistakes whenever σ differs from σ^*, even if the consumers maximize their subjective expected utility. This is consistent with the terminology used in the refi mistake literature.

Lastly, define $v(x) = \sigma(x) u_{buy}(x) + [1-\sigma(x)] u_{wait}(x)$. Hence, v measures the expected welfare of a consumer characterized by x.

Advertising We now consider the effect of advertising exposure a in this environment. With advertising exposure, the welfare of a consumer characterized by x is $v(a,x) = \sigma(a,x) u_{buy}(a,x) + [1-\sigma(a,x)] u_{wait}(a,x)$, and the effect of advertising exposure a on expected experience utility is $\delta(a,x) = v(a,x) - v(0,x)$.

Generally, there are two direct effects of advertising on consumer welfare v.[16] First, advertising can affect U_{buy} and U_{wait}, for example if advertising makes a product more prestigious. Second, advertising can change consumer beliefs $\widetilde{g}_i$, for example if advertising informs the consumer about the benefits of a product. As we explain in more detail below, the first effect is associated with models of persuasive and complementary advertising whereas the second effect is associated with models of informative and deceptive advertising.

In the remainder of this paper we assume that advertising does not enter U_{buy} and U_{wait} and therefor does not affect u_{buy} or u_{wait}. We argue that this assumption is reasonable in the context of mortgage refinancing because refi loans are not consumed and it is unlikely that there are “prestige” effects of refi advertising.

Three Determinants of Welfare Effect

Differential Responsiveness Under the assumption that advertising does not enter U_{buy} and U_{wait}, δ can be expressed as follows:

$$\begin{aligned} \delta(a,x) &= [\sigma(a,x) - \sigma(0,x)] \left[u_{buy}(x) - u_{wait}(x)\right]. \\ &= \Delta\sigma(a,x) \Delta u(x) \end{aligned}$$

It is clear that the effect of advertising on δ depends now solely on its effect on σ and thereby on the probability and severity of mistakes. If advertising has a large effect on σ for x such that $u_{buy}(x) \geq u_{wait}(x)$ and a small effect otherwise then advertising tends to help consumers. The effect of receiving advertising a on consumer welfare depends therefore on the differential in responsiveness of consumers who should buy and those who should wait.

[16]We only consider the direct effects of advertising on consumer welfare, not potential equilibrium effects (e.g. price changes).

Targeting and Intensity of Advertising The expected effect of advertising on a consumer characterized by x is:

$$E\left[\delta\left(a,x\right)|x\right]=\int\delta\left(a,x\right)dF\left(a|x\right).$$

The distribution of advertising F conditional on x captures targeting and intensity of advertising. We sometimes refer to F as the advertising policy. While the intensity of advertising is captured by the unconditional mean of a, targeting describes how the mean varies with x. If F has a lot of mass at 0 for consumers who should wait and a lot of mass at positive levels for consumers who should buy, then advertising tends to help consumers. Advertising intensity only affects the magnitude of $E\left[\delta\left(a,x\right)|x\right]$ whereas targeting also affects the sign.

Consumer Composition Lastly, we have to integrate out x to capture the effect of advertising on all consumers:

$$E\left[\delta\left(a,x\right)\right]=\int\delta\left(a,x\right)dF\left(a|x\right)dG\left(x\right), \tag{1}$$

where G is the distribution of x, which captures that the overall effect of advertising on consumer welfare also depends on the composition of consumers, i.e. how many consumers should buy and how many borrowers should wait and how much they can gain or lose if they decide to buy due to advertising.

Discussion To understand whether advertising is beneficial or harmful all three of these determinants have to be taken into account. For example, it is tempting to ban advertising for a product that would harm the average potential buyer of the product. Examining equation (1), however, makes clear that such a ban might harm consumers, because the effects of differential responsiveness and targeting can dominate the effect of consumer composition. Similarly, if advertisers mostly target consumers who would be harmed by buying the product, this effect can be dominated by the effect of differential responsiveness.

Later, we will try to quantify the contributions of differential responsiveness, targeting and consumer composition to the benefit of advertising $E\left[\delta\left(a,x\right)\right]$. To quantify the importance of differential responsiveness we recalculate the benefit of advertising under a counterfactual σ' such that the average effect of advertising, $\int\Delta\sigma\left(a,x\right)dG\left(x\right)$ remains unchanged, but the effect of advertising under σ' does not vary with x. To quantify the importance of targeting we recalculate the benefit of advertising under a counterfactual targeting policy F' such that the advertising intensity, $\int adF\left(a|x\right)dG\left(x\right)$, remains unchanged but no longer varies with x. To quantify the importance consumer composition we calculate $\int\Delta u\left(x\right)dG\left(x\right)$.

2.2 Empirical Implementation

For most products, it is impossible to measure δ directly because the functions U_{buy} and U_{wait} are unknown.[17] We argue that if the product is a refi loan, U_{buy} and U_{wait} can be measured by the NPV of mortgage payments if the borrower decides to refinance or wait, respectively. The crucial difference between the refi decision and other purchase decisions is that refi loans are not consumed, and refinancing simply replaces one payment stream with another payment stream.

Hence we measure δ as follows:

$$\begin{aligned}\delta(a,r,x) &= [\sigma(a,r,x) - \sigma(0,r,x)]\left[\mathrm{NPV}_{\mathrm{wait}}(r,x;\sigma) - \mathrm{NPV}_{refi}(r,x;\sigma)\right] \\ &= \Delta\sigma(a,r,x)\,\Delta\mathrm{NPV}(r,x;\sigma). \qquad (2)\end{aligned}$$

Here the vector x contains the remaining principal balance, the remaining loan term and the interest rate of the old mortgage and r denotes the current market mortgage rate.[18] $\mathrm{NPV}_j(r,x;\sigma)$ denotes the expected NPV for action $j \in \{\text{wait, refi}\}$ for a borrower characterized by state vector x when the current mortgage rate is r. Note that $\mathrm{NPV}_j(r,x;\sigma)$ depends on σ because the borrower can refinance in the future. Importantly, $\mathrm{NPV}_j(r,x;\sigma)$ includes not only the interest and principal payments but also today's refinancing costs and potential future refinancing costs.[19] NPV_{refi} and $\mathrm{NPV}_{\mathrm{wait}}$ correspond to $-u_{buy}$ and $-u_{wait}$ in our theoretical framework.

We observe the variables in x in our data. However, in addition to the observable state variables, the NPVs likely depend on state variables that are not observable. For example, there could be unobserved differences in the "hassle costs" associated with refinancing. Moreover, there could be unobserved differences in time preferences, risk aversion or future moving propensity. It is likely that these unobservables can rationalize some of the apparent refinancing mistakes that we observe and that have been described in the literature on refi mistakes (e.g. Agarwal, Rosen, and Yao (2015) and Keys, Pope, and Pope (2016)).[20] Later, we will discuss whether such unobserved heterogeneity can affect our estimates of differential responsiveness.

[17] To estimate $u_{buy}(x) - u_{wait}(x)$ we would typically follow a revealed preference approach and *assume* that consumers make no mistakes.

[18] We introduce separate notation for the current mortgage rate because the optimal refinancing policy can be characterized by a trigger mortgage rate.

[19] We provide details about the calculation of $NPV_j(r,x;\sigma)$ in Section 5.

[20] Johnson, Meier, and Toubia (2015) have survey measures of time preferences and risk aversion and find that they cannot explain the failure of households to refinance their mortgage. They also have survey measures of the future moving propensity, which helps to rationalize some of the apparent refinancing mistakes. In one of our robustness checks we allow for heterogeneous moving propensities and find similar estimates of differential responsiveness as in the baseline estimates with a uniform moving propensity.
We find that borrowers who should refinance are more responsive to advertising. This suggests that at least some of these borrowers make mistakes or are inattentive and their failure to refinance despite low interest rates cannot be rationalized by unobservables such as time preferences, risk aversion or future moving propensity.

In section 4 we estimate σ to see whether advertising exposure brings σ closer to an optimal refi policy function σ^*. A borrower would refinance under σ^* if and only if $\Delta\text{NPV}(r,x;\sigma^*) \geq 0$. This optimal policy can be characterized by a trigger rate $r^*(x)$ such that a borrower refinances if $r \leq r^*(x)$ and waits otherwise. Define $d(r,x) \equiv r^*(x) - r$, i.e. d is the difference between the optimal trigger rate and the current mortgage rate. In our responsiveness estimates we let the effect of advertising vary with $d(r,x)$. If advertising has a larger effect for large d, then advertising exposure brings σ closer to $\sigma^*(a,r,x) = 1\{d(r,x) \geq 0\}$.

To calculate $r^*(x)$ we rely on the model of Agarwal, Driscoll, and Laibson (2013) (henceforth ADL). ADL make some simplifying assumptions to obtain a closed form solution for r^* and demonstrate that their trigger rate closely approximates policies that are computed numerically without relying on such simplifying assumptions. We refer to the optimal trigger rate proposed by ADL as $r^*_{ADL}(x)$ and define $d_{ADL}(r,x) \equiv r^*_{ADL}(x) - r$. The ADL trigger rate is also used by Agarwal, Rosen, and Yao (2015) and Keys, Pope, and Pope (2016) to quantify refinancing mistakes.[21] The expression for r^*_{ADL} can be found in Appendix A. In the remainder of this paper we say that a borrower "should refinance" if the market mortgage rate is below the ADL trigger rate and that the borrower "should wait" otherwise.

2.3 Theoretical Advertising Literature

Before we proceed to describing the data, we discuss how models of informative, deceptive, persuasive and complementary advertising can be interpreted in our framework.[22] Readers who are not interested in the relationship to the theoretical advertising literature can jump directly to section 3.

In models of informative and deceptive advertising, advertising affects decision making by changing the beliefs of consumers rather than by changing their utility function. In the context of our framework, this means that informative and deceptive advertising affect $\widetilde{g}_i$ and thereby $\widetilde{u}_{buy}$ and $\widetilde{u}_{wait}$ and σ, but not u_{buy} and u_{wait}.

In models of informative advertising, advertising helps consumers to make more informed decisions. Important references include Marshall (1919), Stigler (1961b), Butters (1977) and Grossman and Shapiro (1984). The informative view suggests that advertising moves $\widetilde{g}_i$ closer to g and therefore advertising tends to help consumers make better decisions. However, this is not necessarily the case. For example, suppose $\widetilde{g}_i$ is a belief about future interest rates and the fixed cost

[21]Conceptually, there is a "model free" alternative to study refinancing mistakes by simply comparing the realized streams of mortgage payments of borrowers who refinanced and those who did not. In practice, however, this approach would require data over a very long time period to ensure that the realized path of mortgage rates approximates rational expectations. For example, the mortgage rates were decreasing over the first half of our sample period so the mistakes of borrowers who failed to refinance during this time appeared "right" ex post.

[22]See the excellent surveys by Bagwell (2007) and Renault (2015) for more detailed discussion of these models.

of refinancing. We could construct a $\widetilde{g}_i$ that deviates substantially from g such that the resulting $\widetilde{u}_{buy}$ and $\widetilde{u}_{wait}$ are close to u_{buy} and u_{wait} and the consumer therefore makes approximately optimal decisions. This would be the case if the consumer has overly optimistic beliefs about the interest rate, but overly pessimistic beliefs about the fixed cost of refinancing and these two biases approximately offset each other. If informative advertising corrects the consumer's belief about interest rates, but not the belief about the fixed cost of refinancing, it would move $\widetilde{g}_i$ closer to g, but would lead to worse decisions.

More recently, a literature on deceptive advertising has emerged, which stresses that advertising can distort decision making because it informs consumers only selectively and tries to affect how the information is perceived.[23] Deceptive advertising might move $\widetilde{g}_i$ further away from g, which suggests that it leads to worse decisions. However, this is not necessarily the case, because we have argued above that beliefs that are further from g can lead to better decisions.

In models of persuasive and complementary advertising, advertising affects consumer preferences. Persuasive advertising changes consumer preferences, whereas complementary advertising enters as an argument in a stable utility function.

Persuasive advertising can be interpreted in two ways with different welfare implications. Under the first interpretation the pre-advertising preferences are the consumer's true preferences and the relevant standard for consumer welfare whereas the post-advertising preferences explain the consumer's choices, which can therefore be distorted. This distortionary interpretation goes back to Braithwaite (1928). In the context of our framework, the distortionary interpretation says that advertising affects $\widetilde{u}_{buy}$ and $\widetilde{u}_{wait}$ and thereby σ, but not u_{buy} and u_{wait}. Hence, the distortionary interpretation of persuasive advertising can be regarded as "reduced form" of models of informative and especially models of deceptive advertising without specifying consumer beliefs $\widetilde{g}_i$. Under the second interpretation, the post-advertising preferences are the relevant standard for consumer

[23] Akerlof and Shiller (2015) ("Advertising as Storytelling") emphasize this aspect: "... It's not just that we acquire new 'information'; we change our point of view and interpret information in new ways. Importantly, these evolutions of our thoughts mean that our opinions, and the decisions that are based on them, may be quite inconsistent. These descriptions of human thinking as narrative, or like narrative — so that it will not naturally, inevitably, be consistent—gives a role for advertising." On the role of advertisers they write: "...advertisers are supposed to enhance the sales of the companies that hire them, even if those sales reduce consumers' well being."

See also Kaldor (1950): "As a means of supplying information it may be argued that advertising is largely biased and deficient. Quite apart from the making of deliberately faked claims about products which legislation and professional etiquette have never succeeded in suppressing, the information supplied in advertisements is generally biased, in that it concentrates on particular features to the exclusion of others; makes no mention of alternative sources of supply; and it attempts to influence the behavior of the consumer, not so much by enabling him to plan more intelligently through giving more information, but by forcing a small amount of information through its sheer prominence to the foreground of consciousness."

Nelson (1974) who develops models a model informative advertising discusses deceptive advertising informally. Recently, formal models of deceptive advertising have been studied by Glaeser and Ujhelyi (2010), Hattori and Higashida (2012), Hattori and Higashida (2014), Corts (2014), Piccolo, Tedeschi, Ursino, et al. (2015), Piccolo, Tedeschi, and Ursino (2015) and Rhodes and Wilson (2015).

welfare and therefore advertising is not distorting the choices. In the context of our framework, the non-distortionary interpretation says that advertising changes $\left(U_{buy}, U_{wait}\right)$ and therefore has similar effects on $\left(\widetilde{u}_{buy}, \widetilde{u}_{wait}\right)$ and $\left(u_{buy}, u_{wait}\right)$.

Lastly, in models of complementary advertising, advertising enters as an argument in a stable utility function (Stigler and Becker (1977), Nichols (1985) and Becker and Murphy (1993)). For example, these models can capture the prestige effects of advertising. In our framework, this means that complementary advertising enters as an argument in $\left(U_{buy}, U_{wait}\right)$ and therefore therefore has similar effects on $\left(\widetilde{u}_{buy}, \widetilde{u}_{wait}\right)$ and $\left(u_{buy}, u_{wait}\right)$. Hence, complementary advertising is similar to the the non-distortionary interpretation of persuasive advertising.

We assume that refi advertising does not enter U_{buy} and U_{wait}. Hence, we rule out models of complementary advertising and the nondistortionary interpretations of persuasive advertising. Our framework is consistent with models of informative and deceptive advertising. It is also consistent with the distortionary interpretation of persuasive advertising, which can be regarded as a reduced form of models of informative and especially deceptive advertising without specifying consumer beliefs $\widetilde{g}_i$.

It is plausible that models of informative and deceptive advertising apply to refi advertising. On the one hand, refi advertising reminds borrowers of their refi option and perhaps of the current mortgage rate. On the other hand, refi advertising can often be considered to be deceptive. For example, refi ads often advertise the reduction in monthly payments without explaining that this reduction is partly achieved through term extension rather than through a reduction of the interest rate.[24]

3 Data

Data Description To quantify the effect of advertising on borrower welfare and to determine the importance of differential responsiveness, targeting and borrower composition is challenging because available data sets do not contain the necessary information. Existing data sets do not provide information about refinancing behavior, borrower and loan characteristics, and advertising exposure at the borrower level. Data on mortgage loans and mortgage borrowers do not contain information about a borrower's exposure to refinance advertising, and data on advertising do not contain information about a borrower's refinancing behavior.

Typical loan-level mortgage data sets, such as McDash loan servicing data (formerly Lender Processing Service), only provide information about loan characteristics. Loan-level data alone do

[24] The FTC warns consumers specifically about deceptive mortgage advertising and explains "What the Ads Say" and "What the Ads Don't Say" (http://www.consumer.ftc.gov/articles/0087-deceptive-mortgage-ads). Under the Consumer Financial Protection Act the Consumer Financial Protection Bureau (CFPB) is authorized to take action against deceptive lending acts.

not allow us to determine whether a loan was refinanced or prepaid for a different reason, because they only track loans, not borrowers. Moreover, the McDash data contain a borrower's credit score at loan origination, but not her updated credit score, which is one of the important characteristics that determine whether the borrower would qualify for a refi loan. Borrower-level panel data from Credit Risk Insight Servicing McDash (CRISM) combines credit bureau data from Equifax and the loan-level McDash data. Therefore it provides information about a borrower's updated credit score and whether a borrower prepaid a loan to refinance. However, the CRISM data only provide information about borrower and loan characteristics and refinancing behavior but not about advertising exposure.

Although data on mass advertising such as TV, newspaper and radio advertising is readily available, it is not suitable for this study because we want to link borrower-level advertising exposure, to borrower and loan characteristics and to subsequent refinancing behavior. Therefore, the direct-mail advertising data from Mintel Comperemedia (henceforth Mintel) is more suitable for this study.[25] The main limitation of direct-mail advertising data is that the recipient's purchase behavior is typically not observed.

We obtain information on borrower and loan characteristics, refinancing behavior and advertising exposure at the borrower level, by merging the CRISM and Mintel data sets. We are able to match a borrower in the Mintel and her record in CRISM based on the three common variables contained in both data sets: a borrower's age, zipcode and exact outstanding mortgage loan balance in a given month.[26] We consider a match successful only when two observations in the two data sets have exactly identical values.

Our final sample consists of 12,435 borrower-month pairs from 2009 to 2015 for which we observe advertising exposure. All borrowers have a fixed-rate mortgage. We exclude borrowers with FICO scores below 620 and borrowers with loan-to-value ratios above 0.8.[27] These borrowers are excluded because they might not qualify for a refi loan, and we do not want to confuse ineligibility to refinance with refi mistakes.

Summary Statistics Table 1 shows summary statistics for two groups of borrowers depending on values of $r^*_{ADL}(x) - r$. Recall, that we refer to borrowers with $r^*_{ADL}(x) < r$ as those who "should wait" and borrowers with $r^*_{ADL}(x) \geq r$ to those who "should refinance".

The variables are divided into five groups. The first group of variables are dummy variables that indicate whether the borrower refinanced. If a borrower decides to refinance, it can take several

[25] Recent studies using the Mintel data include Han, Keys, and Li (2015), Ru and Schoar (2016) and Grodzicki (2015).

[26] Our version of the Mintel data set is merged to credit bureau data from TransUnion and therefore contains information about the outstanding mortgage loan balance.

[27] We approximate a borrower's updated house value using the house value at loan origination and a county-level house price index provided by CoreLogic.

months before the refi loan is closed and several additional months before we observe that the borrower has refinanced in the data. "Refinanced within *n* Quarters" is a dummy variable that equals to one if a borrower refinances within *n* quarters after we measure the advertising exposure. Note that these variables are equal to one if a borrower refinances with any mortgage lender, not just with the advertising lender. Hence, our estimates incorporate the spillover effects of advertising, which is important if we want to study the effects of advertising on consumer welfare, rather than the profitability of advertising. The table shows that borrowers who should refinance, do refinance at approximately twice the rate as borrowers who should wait. However, 8% of the borrowers who should wait refinance within three quarters and 85% of the borrowers who should refinance fail to do so.

The second group of variables contains two measures of advertising exposure. The first measure counts all direct-mail advertising. A borrower receives 0.23 direct-mail refinance pieces in the previous month on average. In other words, a borrower receives approximately one piece of refi advertising every four months. Moreover, borrowers who should refinance receive 50% more advertising than those who should wait, which suggests that advertisers target borrowers who should refinance. However, notice that there are 10,941 borrowers who should wait and only 1,494 borrowers who should refinance. Consequently, about 83% of all refi ads are sent to borrowers who should wait.[28] The second measure of advertising exposure count only direct mail refi advertising that is sent by specialized mortgage companies such as Quicken Loans, as opposed to depository institutions such as Wells Fargo. Specialized mortgage firms account for approximately about 50% of the total.

[28]The fraction of all refi ads sent to those who should wait can be calculated as follows: $0.83 = \frac{0.22*10941}{0.22*10941+0.33*1492}$.

Table 1: **Summary Statistics.** Column (1) shows the mean for borrowers who should wait according to the optimal trigger rate by ADL; column (2) shows borrowers who should refinance; and column (3) shows the unconditional mean. The first group of variables shows how many households refinanced in the subsequent quarters. The second group contains two measures of advertising exposure. First, the total number of direct mail refi ads a household received in the previous month. Second, the number of refi ads from nonbanks. The third group are the variables in x that determine the optimal trigger rate $r^*_{ADL}(x)$, and the prevailing rate mortgage rate r. The fourth group is the optimal trigger rate $r^*_{ADL}(x)$ proposed by ADL, the difference between the optimal trigger rate and the available mortgage rate $d_{ADL}(r,x) = r^*_{ADL}(x) - r$, and a dummy variable $d_{ADL}(r,x) \geq 0$, which indicates whether the borrower should refinance based on the ADL model. Lastly, the fifth group contains other controls. We exclude borrowers with loan to value ratios above 0.8 or FICO scores below 620.

	Should Wait	**Should Refinance**	**Total**
Group 1: Refi Behavior			
Refinanced within 1 Quarter	0.03	0.06	0.03
Refinanced within 2 Quarters	0.05	0.11	0.06
Refinanced within 3 Quarters	0.08	0.16	0.09
Refinanced within 4 Quarters	0.11	0.20	0.12
Group 2: Advertising Exposure			
Direct Mail Advertising (DMA)	0.22	0.33	0.23
DMA: Nonbanks	0.11	0.22	0.13
Group 3: x and r			
Remaining Principal Balance (in \$1,000)	106.07	124.04	108.22
Remaining Term (in Months)	225.34	258.92	229.37
Rate of Current Mortgage (in %)	5.14	6.74	5.33
Market FRM Rate (in %)	4.29	3.97	4.25
Group 4: Optimal Refi Policy			
Optimal Trigger Rate (in %)	2.51	4.65	2.77
Optimal Trigger Rate - Market Rate (in %)	-1.78	0.69	-1.49
Should Refinance	0.00	1.00	0.12
Group 5: Controls			
Mortgage Inquiries (Past 3 Months)	0.06	0.10	0.06
FICO Score	774.90	751.27	772.06
LTV Ratio	0.47	0.55	0.48
Income (in \$1,000)	80.83	75.95	80.25
Age	54.33	54.85	54.39
Observations	10943	1492	12435
Fraction of Total	88%	12%	100%

The third group of variables contains x and r. The optimal trigger rate $r^*_{ADL}(x)$ depends on the remaining principal balance, the remaining mortgage term, and the interest rate of the current mortgage. It is increasing in all three of these state variables. It is increasing in the remaining principal, because the interest savings are proportional to the principal but part of the refinancing costs are fixed. It increasing in the remaining loan term because if the remaining loan term is short the borrower has to pay the high mortgage rate on the old loan only for a short period of time. Naturally, it is also increasing in the interest rate of the old mortgage. Consequently, borrowers who should refinance have higher remaining balances, longer remaining loan terms and higher interest rates on their current mortgage. The available mortgage rate i, is the average mortgage rate for 30 year fixed rate mortgages provided by the St. Louis Fed.[29] Unsurprisingly, borrowers who should refinance face lower mortgage rates.

The fourth group of variables are generated using the optimal refinancing model by ADL, the optimal trigger rate $r^*_{ADL}(x)$, the gap between the optimal trigger rate and the market rate $d_{ADL}(r,x)$ and an indicator called "Should Refinance" for $d_{ADL}(r,x) \geq 0$. If it is not optimal for the borrower to refinance at any positive interest rate based on the ADL model, we set $r^*_{ADL}(x)$ to zero.[30] While the market rate is about one percentage point below the rate of the current mortgage on average, it is about 1.5 percentage points above the optimal trigger rate. Indeed, only 12 percent of the borrowers should refinance according to the ADL trigger rate. The optimal trigger rate is 2.51 percent on average for borrowers who should wait and 4.65 percent for borrowers who should refinance.

The fifth group includes additional controls that might affect a borrower's refinancing behavior. The number of mortgage inquiries recorded by the credit bureau in the previous three months could capture whether a borrower is already looking for a refi loan. Borrowers who are already looking for a refi loan are more likely to refinance regardless of advertising exposure. In addition, we also consider the FICO score, the LTV ratio, income and age because they can determine whether a borrower qualifies for a mortgage.

Table 2 splits the sample further. It shows borrowers who should wait in columns (1) and (2) and borrowers who should refinance in columns (3) and (4). Within each group of borrowers, it compares borrowers who did not receive advertising (columns (1) and (3)) with borrowers who received advertising (columns (2) and (4)). For borrowers who should wait, advertising appears to have a small effect on the probability of refinancing. The probability that the borrower refinances within two, three or four quarters is one percentage point higher for borrowers who received advertising, and there is no difference in the probability of refinancing within one quarter. For borrowers who should refinance, however, advertising appears to have a larger effect on the probability of refinancing. The refi probability is between four and five percentage points higher for borrowers who received advertising over a horizon of two, three or four quarters and two percentage points higher

[29] The data is available at https://fred.stlouisfed.org/series/MORTGAGE30US. In a robustness check, we allow different borrowers to have access to different interest rates to account for possible differences in default risk or mortgage shopping costs.

[30] This is the case for 8.5% of all observations.

over a horizon of a single quarter. This suggests that borrowers who should refinance are more responsive to advertising. In the next section, we present responsiveness estimates that control for other determinants of refinancing behavior and confirm this suggestive evidence.

4 Differential Responsiveness

Specification In this section we estimate the refinancing policy σ. To facilitate comparisons with specifications where we instrument for advertising, we estimate a linear probability model rather than a nonlinear binary choice model:

$$refinanced = \beta_0 + \beta_1 d_{ADL}(x,r) \times a + \beta_2 a + \beta_3 d_{ADL}(x,r) + Z\beta_Z + \xi_c + \xi_q + \varepsilon. \quad (3)$$

The dependent variable is a dummy that is equal to one if a borrower refinances within the following three quarters.[31] Recall that $d_{ADL}(x,r)$ measures the gap between the optimal trigger rate $r^*_{ADL}(x)$ and the market mortgage rate r. If the borrower follows the optimal ADL refi strategy, she should exercise her refinancing option if $d_{ADL}(x,r)$ is positive and wait if $d_{ADL}(x,r)$ is negative. The magnitude of $d_{ADL}(x,r)$ tells us how far the borrower is in the exercise region or the waiting region, respectively. The variable a is the number of refinance advertising mailings the borrower received in the previous month. The main coefficient of interest is β_1 for the interaction term $d_{ADL}(x,r) \times a$. The variables in Z are included to control for borrower and loan characteristics, which include the borrower's age, current FICO score, current LTV ratio and the number of mortgage inquiries within the past three months.[32] Recall that we exclude borrowers with a FICO score below 620 or LTV ratio above 0.8 because such borrowers might be ineligible for refinancing. In addition, we control for the FICO score and the LTV ratio account for the fact that it might be easier to qualify for a refi loan for borrowers with good credit scores and low LTV ratios. Moreover, the number of mortgage inquiries within the past three months is included in order to control for borrowers who have recently looked for a refinancing option. It is important to control for recent mortgage inquiries because lenders might target borrowers who are already in the market for refinancing and the estimated effects of advertising could therefore be driven by reverse causality. Lastly, we include county and quarter fixed effects ξ_c and ξ_q.[33]

[31] Later we show that our results are similar if we consider refinancing within one, two or four quarters instead.

[32] For a subsample of borrowers we also observe education and occupation but we found these not to be important for refinancing behavior.

[33] In more recent years the Mintel sample includes respondents who are panelists, whereas the sample was a repeated cross-section in earlier years. Therefore we also experimented with specifications with borrower fixed effects. However, we only have within borrower-variation for some borrowers. These estimates therefore rely heavily on the functional form of the linear probability model and should be interpreted with caution. We also estimated specifications with county-quarter fixed effects, which suffer from a similar problem. The estimates of β_1 in these two

Table 2: **Sample Means by Should Wait / Refinance and Advertising Exposure.** Columns (1) and (2) show the mean for borrowers who should wait according to the optimal trigger rate by ADL and columns (3) and (4) show borrowers who should refinance. Columns (1) and (3) show borrowers shows borrowers who did not receive refi ads and columns (2) and (4) shows borrowers who did receive refi ads. We exclude borrowers with loan to value ratios above 0.8 or FICO scores below 620.

	Should Wait		**Should Refinance**	
	(1) No Ads	(2) Ads	(3) No Ads	(4) Ads
Group 1: Refi Behavior				
Refinanced within 1 Quarter	0.03	0.04	0.06	0.08
Refinanced within 2 Quarters	0.05	0.07	0.10	0.15
Refinanced within 3 Quarters	0.08	0.09	0.15	0.19
Refinanced within 4 Quarters	0.11	0.12	0.19	0.23
Group 2: Advertising Exposure				
Direct Mail Advertising (DMA)	0.00	1.41	0.00	1.52
DMA: Nonbanks	0.00	0.72	0.00	0.98
Group 3: x and r				
Remaining Principal Balance (in $1,000)	101.47	130.78	120.00	138.49
Remaining Term (in Months)	222.55	240.31	258.03	262.09
Rate of Current Mortgage (in %)	5.18	4.93	6.86	6.34
Market FRM Rate (in %)	4.32	4.17	4.00	3.85
Group 4: Optimal Refi Policy				
Optimal Trigger Rate (in %)	2.48	2.69	4.71	4.43
Optimal Trigger Rate - Market Rate (in %)	-1.84	-1.48	0.72	0.58
Should Refinance	0.00	0.00	1.00	1.00
Group 5: Controls				
Mortgage Inquiries (Past 3 Months)	0.05	0.08	0.10	0.09
FICO Score	775.37	772.40	752.06	748.44
LTV Ratio	0.46	0.51	0.54	0.58
Income (in $1,000)	79.90	85.86	73.94	83.16
Age	54.39	54.03	55.02	54.24
Observations	9225	1718	1166	326
Fraction of Total	74%	14%	9%	3%
Conditional Prob. of Receiving Advertising	84%	16%	78 %	22 %

Endogeneity Identification of the effects of advertising on demand is challenging because of the possibility that advertisers target consumers who are inherently more likely to purchase an advertised product. If an advertiser has more information than researchers about which consumers are more or less likely to purchase the product, then advertising might be targeted at consumers with high demand for the product even after controlling for characteristics that are observed by the researchers. In this case, there is a concern about reserve causality: even if advertising has no effect on a consumer's demand we would find a relationship between advertising and demand. Notice that while this reverse causality concern would lead to an upward bias of the overall effect of advertising, it is unclear whether β_1, which measures differential responsiveness, would be biased and in which direction the bias would go. This is important, because we are more interested in differential responsiveness than the average effect of advertising.

In our setting, the concern about targeting based on unobserved borrower characteristics is less serious than in other settings, because we observe more information about borrowers than most lenders. Even if a lender has an existing relationship with a mortgage borrower through loan servicing, the information about the borrower is likely limited to her mortgage characteristics and payment behavior, which we also observe. In addition, we also observe a borrower's updated FICO score, which contains information, not only about the payment behavior for the mortgage but also other accounts such as credit cards and auto loans.[34]

An instance in which a lender may have more information about a borrower than we observe is when the lender has an ongoing relationship with the borrower through other products, for example, checking accounts. Such lenders might be able to observe how a borrower's income or assets have evolved over time. Because we observe a borrower's annual income, the amount of information unobserved in our data is likely limited and we do not know whether using this information for targeted advertising would be legal. Nevertheless, this possibility still raises the issue of reverse causality.

We address this reverse causality concern by using direct mailings by specialized mortgage companies as an instrumental variable for the total number of direct mailings . The idea is that lenders who likely have an additional ongoing relationship with the borrower are depository institutions, which usually have multiple lines of business. For example, banks like Wells Fargo offer numerous financial services to consumers such as checking and savings accounts, wealth management, etc. In contrast, most specialized mortgage companies, such as Quicken Loans, usually

specifications are 0.0133 and 0.0146, which is similar to our baseline specification.

[34] Lenders can target borrowers who are likely to refinance by purchasing a list of borrower addresses from credit bureaus that satisfy certain conditions. For example, lenders can select borrowers who have mortgages with outstanding balances and monthly payments above certain thresholds. Moreover, a lender might even ask for a list of borrowers with a positive number of mortgage inquires in the past months to target advertising to those who are already looking for a refi loan. As we observe these variables, this kind of targeting should not create a reverse causality concern for our estimates.

only have a mortgage origination and perhaps mortgage servicing business. Thus, these lenders are unlikely to have information about borrowers that we do not observe in our data As shown in Table 1, direct mailings from nonbank lenders make up slightly more than a half of the total direct mailings received in our sample.

In the next section we present our results. The baseline estimates are from the OLS regression of equation (3), and we present IV estimates as a robustness check after discussing the baseline estimates.

Results Table 3 shows the baseline estimates. The first column presents estimates with a specification without the interaction term $d_{ADL}(x,r) \times a$, while the second column presents the estimates with the specification given in equation (3). In the first column we find that the effect of advertising on demand is small and barely statistically significant on average. This is consistent with Lewis and Rao (2015), who show that it is generally difficult to estimate the returns to advertising precisely. However, turning to the second column, we find that the effect of advertising is very heterogeneous and depends on $d_{ADL}(x,r)$. Borrowers who are further in the exercise region are more responsive to advertising. If the market mortgage rate equals the trigger rate where it becomes optimal to refinance based on the ADL model, one piece of direct mail advertising increases the probability of refinancing by 2.50 percentage points or about 15% of the unconditional refinancing probability of those with $d_{ADL}(x,r) \geq 0$. If the market mortgage rate is one percentage point above the ADL trigger rate, i.e. the borrower should wait, the effect decreases by 1.59 to 0.91 percentage points. Conversely, if the market mortgage rate is one percentage point below the ADL optimal trigger rate, i.e. the borrower should refinance, the effect increases by 1.59 to 4.09 percentage points.

This result suggests that advertising is potentially beneficial for borrowers. The estimated heterogeneous effects of advertising will help to mitigate mistakes of those borrower who fail to take advantage of low interest rates. At the same time, advertising is unlikely to exacerbate mistakes of premature refinancing for those who would not benefit from refinancing. As discussed in section 2, however, differential responsiveness is just one of the factors that determine the net effect of advertising on borrower welfare. Borrower welfare also depends on targeting and the composition of borrowers, which we will take into account in section 5.

Our finding suggests that the recipients of refi ads respond more to the informative aspects of refi ads than to the deceptive aspects. In particular our finding is consistent with a model in which advertising increases the probability that borrowers are attentive. Inattentive borrowers fail to take advantage of lower mortgage rates because do not consider the possibility of refinancing. However, while models of informative advertising might be a more natural interpretation of the findings, we cannot reject models of deceptive advertising without imposing further restrictions. In particular, the findings are consistent with a model of deceptive advertising in which borrowers who should refinance are more easily deceived than those who should wait and deceptive advertising therefore increases borrower well-being. Before we proceed to Section 5, we briefly present several robustness check for our responsiveness estimates.

Table 3: **Responsiveness: Baseline Estimates.** The dependent variable is a dummy that is equal to one if the borrower refinanced within three quarters. County and quarter fixed effects are included. Standard errors are clustered at the county level.

(Optimal Trigger - Market Rate) x (Direct Mail Adv.)		0.0159***
		(0.00415)
Direct Mail Advertising (DMA)	0.0100*	0.0250***
	(0.00607)	(0.00823)
Optimal Trigger Rate - Market Rate (in %)	0.0373***	0.0344***
	(0.00357)	(0.00353)
Mortgage Inquiries (Past 3 Months)	0.0890***	0.0893***
	(0.0154)	(0.0155)
FICO Score	0.000264***	0.000269***
	(0.0000708)	(0.0000707)
LTV Ratio	-0.0443**	-0.0438**
	(0.0198)	(0.0198)
Income (in $1,000)	0.000332***	0.000334***
	(0.0000961)	(0.0000961)
Age	-0.000522	-0.000532
	(0.000329)	(0.000329)
Constant	-0.103	-0.111*
	(0.0643)	(0.0639)
Observations	11597	11597

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

IV Estimates We use mailings from nonbank lenders as an IV to address a potential reverse causality issue. The two-stage least squares estimates are shown in Table 4 and the first stage estimates in Table 11 in the Appendix. The results are similar to the baseline estimates.

Table 4: **Responsiveness: IV Estimates.** Two stage least squares estimates using direct mail advertising by specialized mortgage firms as an instrument for direct mail advertising. The first stage regressions are shown in Table 11 in the Appendix. County and quarter fixed effects are included. Standard errors are clustered at the county level.

(Optimal Trigger - Market Rate) x (Direct Mail Adv.)		0.0140^{***}
		(0.00456)
Direct Mail Advertising (DMA)	0.0119	0.0235^{**}
	(0.00834)	(0.0105)
Optimal Trigger Rate - Market Rate (in %)	0.0373^{***}	0.0348^{***}
	(0.00359)	(0.00361)
Mortgage Inquiries (Past 3 Months)	0.0890^{***}	0.0892^{***}
	(0.0154)	(0.0154)
FICO Score	0.000264^{***}	0.000269^{***}
	(0.0000709)	(0.0000709)
LTV Ratio	-0.0445^{**}	-0.0439^{**}
	(0.0198)	(0.0197)
Income (in \$1,000)	0.000331^{***}	0.000334^{***}
	(0.0000959)	(0.0000958)
Age	-0.000522	-0.000531
	(0.000328)	(0.000329)
Observations	11396	11396

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dummy for Optimal Refi Policy Column (1) in Table 5 replaces $d_{ADL}(x,r)$ with an the dummy variable $\mathbf{1}\{d_{ADL}(x,r) \geq 0\}$. This specification takes the ADL optimal refi policy "more seriously".

The estimates in column (1) imply that advertising has no effect on borrowers who should wait but increases the refi probability of borrowers who should refinance by approximately 3.8 percentage points or about 24% of the unconditional refi probability of borrowers with $\mathbf{1}\{d_{ADL}(x,r) \geq 0\}$. These estimates support our interpretation of the baseline estimates and rules out the possibility that the positive coefficient on $d_{ADL}(x,r)$ simply reflects differences in the refi probability within the groups $d_{ADL}(x,r) \geq 0$ and $d_{ADL}(x,r) < 0$, rather than different refi probabilities for these two groups. An advantage of these estimates compared to the baseline estimates is that they do not imply a negative effect of advertising, even for borrowers with very negative $d_{ADL}(x,r)$. In columns (2) and (3) we include the dummy $\mathbf{1}\{d_{ADL}(x,r) \geq 0\}$ and $d_{ADL}(x,r)$. In these specifications $d_{ADL}(x,r)$ appears to explain refinancing behavior better than $d_{ADL}(x,r) \geq 0$.

Table 5: **Dummy for Optimal Refi Policy.** Using the variable Should Refinance, which is equal to one if the borrower should refinance, i.e. $\mathbf{1}\{d_{ADL}(x,r) \geq 0\}$. County and quarter dummies are included. Standard errors are clustered at the county level.

	(1)	(2)	(3)
Should Refinance x (Direct Mail Adv.)	0.0381**	0.0448***	0.0241
	(0.0165)	(0.0163)	(0.0192)
(Optimal Trigger - Market Rate) x (Direct Mail Adv.)			0.0105**
			(0.00429)
Direct Mail Advertising (DMA)	0.00420	0.000418	0.0147
	(0.00584)	(0.00556)	(0.00916)
Should Refinance	0.0656***	-0.000752	0.00357
	(0.0154)	(0.0165)	(0.0165)
Optimal Trigger Rate - Market Rate (in %)		0.0356***	0.0339***
		(0.00359)	(0.00354)
Mortgage Inquiries (Past 3 Months)	0.0913***	0.0896***	0.0895***
	(0.0157)	(0.0155)	(0.0155)
FICO Score	0.000224***	0.000271***	0.000274***
	(0.0000709)	(0.0000706)	(0.0000706)
LTV Ratio	0.0656***	-0.0411**	-0.0410**
	(0.0156)	(0.0200)	(0.0200)
Income (in $1,000)	0.000378***	0.000336***	0.000337***
	(0.0000942)	(0.0000953)	(0.0000953)
Age	-0.000301	-0.000513	-0.000523
	(0.000325)	(0.000328)	(0.000328)
Constant	-0.200***	-0.112*	-0.117*
	(0.0611)	(0.0633)	(0.0631)
Observations	11597	11597	11597

Standard errors in parentheses

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Further Robustness Checks Appendix C presents further robustness checks. We consider alternative parameters for the ADL trigger rate (Table 17), include interaction terms between borrower characteristics such as age and income with advertising and $d_{ADL}(x,r)$ (Table 18), allow for heterogeneous moving propensity across borrowers (Table 19), heterogeneous mortgage rates across borrowers (Table 21), and vary the time window after advertising exposure (Table 22). The finding that borrowers who should refinance are more responsive to advertising is robust to these changes.

5 Advertising Benefit and Targeting Counterfactuals

In this section, we calculate the effect of advertising on borrower welfare $E\left[\delta(a,r,x)\right]$. Recall that δ is defined as follows:

$$\begin{aligned}\delta(a,r,x) &= \left[\sigma(a,r,x)-\sigma(0,r,x)\right]\left[\mathrm{NPV}_{\mathrm{wait}}(r,x;\sigma)-\mathrm{NPV}_{refi}(r,x;\sigma)\right] \\ &= \Delta\sigma(a,r,x)\,\Delta NPV(r,x;\sigma).\end{aligned} \tag{4}$$

First, we explain how we calculate the expected NPV of mortgage payments for each borrower to obtain $\Delta NPV(r,x;\sigma)$. We then obtain $\Delta\sigma(a,r,x)$ from our responsiveness estimates in the previous section and combining these two parts allows us to calculate $E\left[\delta(a,r,x)\right]$. Next, we quantify how borrower composition, targeting and differential responsiveness affect $E\left[\delta(a,r,x)\right]$. Finally, we simulate the effect of a counterfactual targeting policy, to study how much borrower welfare could be enhanced with better targeting.

5.1 Calculating Expected NPV

We calculate $NPV_j(i_t,x_t;\sigma)$ for $j\in\{refi,wait\}$ as follows:

$$\begin{aligned}NPV_j(r_t,x_t;\sigma) &= p_j(r_t,x_t) \\ &+ \beta E\left[\sum_{t'=t+1}^{T}\left\{pr_{move}u_{move}(x_{t'})+(1-pr_{move})\sum_{j\in\{refi,wait\}}\sigma_j(r_{t'},x_{t'},0)p_j(r_{t'},x_{t'})\right\}\middle| r_t,x_t\right]\end{aligned} \tag{5}$$

where the expectation is taken over realizations of future mortgage rates $r_{t'}$ and loan characteristics $x_{t'}$. Future loan characteristics $x_{t'}$ are determined in part by a borrower's future decision to refinance as prescribed by her policy function σ. This means that we are allowing for the possibility that a borrower refinances in period $t'>t$ even if she does not refinance in period t. Notice that we use σ rather than the optimal refi policy σ^* to calculate the net present value, because it would be unrealistic to assume that the borrower follows the optimal strategy in the future. For simplicity, we hold additional characteristics, such as the borrower's age, FICO score and house price fixed in the future. We assume that the annual discount rate is 5 percent, which implies that $\beta=\left(\frac{1}{1.05}\right)^{\frac{1}{12}}$.

The first term $p_j(r_t,x_t)$ denotes the payment a borrower has to make depending on her action j. If $j=wait$, then $p_{wait}(r_t,x_t)$ is equal to the monthly payment with the existing mortgage. If $j=refi$, then $p_{refi}(r_t,x_t)$ is the sum of the new monthly payment as a result of refinancing and the cost of refinancing, which we set equal to $2,000 plus 1% of the remaining principal following Agarwal, Driscoll, and Laibson (2013). Next, pr_{move} and $u_{move}(x_{t'})$ refer to the probability and payoff from moving, respectively. Following Agarwal, Driscoll, and Laibson (2013), we assume that borrowers move with a probability of 10% each year and that if a borrower moves she must pay the remaining principal balance in one lump-sum payment. Thus, $u_{move}(x_{t'})$ is equal to the remaining principal balance in period t'.

The fact that the stream of a future mortgage payments depends on σ allows for the possibility that the borrower refinances in a period later than t. We assume that the number of refi ads a in the future is zero, so the probability of refinancing in future periods is $\sigma_j(r_{t'}, x_{t'}, 0)$. We make this assumption because it is difficult to estimate the stochastic process that governs the evolution of advertising a with our data. Moreover, to avoid predicted probabilities outside of $[0,1]$, we use a logit estimates of σ, which are shown in Table 13 in Appendix B instead of the estimates from the linear probability model presented in the previous section.[35]

Calculating $NPV_j(r_t, x_t; \sigma)$ exactly is difficult because of the large number of possible future states involved in the calculation. Thus, we approximate $NPV_j(r_t, x_t; \sigma)$ by averaging simulated mortgage payments for simulations of future paths of $\{(r_{t'}, x_{t'})\}_{t'=t+1}^{T}$ given (r_t, x_t).

To model the evolution of the mortgage rate we follow Campbell and Cocco (2015) and estimate the following AR(1) process:

$$\log(1+r_t) = \alpha_0 + \alpha_1 \log(1+r_{t-1}) + \varepsilon_t,$$

where r_t is the rate for 30 year fixed rate mortgages, t is a month between 1971 and 2015 and ε_t is a normally distributed error term. We estimate $\widehat{\alpha_0} = 0.000117$ and $\widehat{\alpha_1} = 0.998$ so this process reverts back to its mean $\frac{\widehat{\alpha_0}}{1-\widehat{\alpha_1}} = 0.0530$, which corresponds to a mortgage rate of 5.44%. The standard deviation of ε_t is estimated to be 0.00255.

Note that the loan characteristics in x_t other than the remaining balance will change only if a borrower refinances. Without refinancing, the remaining balance evolves in a deterministic way, following the standard mortgage amortization schedule for a fixed rate mortgage. If a borrower refinances, the evolution of future remaining balances changes slightly because of a change in the interest rate of the loan.

Lastly, we simulate paths for $\{(r_{t'}, x_{t'})\}_{t'=t+1}^{T}$ and then obtain $\Delta NPV(r, x; \sigma)$ by averaging over the simulated paths.

[35] We also omit county and quarter fixed effects from the specification used for the future refi policy, because we have only few observations for most counties and some quarters and can therefore not consistently estimate the fixed effects. Notice however, that we use our baseline estimates to calculate $\Delta\sigma(a, r, x)$ in equation (4), because the fixed effects cancel out in this difference and predicted refi probabilities outside of $[0,1]$ are not problematic.

5.2 The Effect of Advertising on Borrower Welfare

In this subsection we calculate $E[\delta(a,r,x)]$ by combining $\Delta\sigma(a,r,x)$ and $\Delta NPV(r,x;\sigma)$, and then study the roles of borrower composition, targeting and differential responsiveness. First, to quantify the importance consumer composition we calculate $\int \Delta NPV(r,x;\sigma)dG(r,x)$. Second, to quantify the importance of targeting we recalculate the benefit of advertising under a counterfactual targeting policy F' such that the average advertising intensity $\int adF(a|x)\,dG(x)$ remains unchanged but no longer varies with x. Third, to quantify the importance of differential responsiveness we recalculate the benefit of advertising under a counterfactual σ' such that the average effect of advertising $\int \Delta\sigma(a,x)\,dG(x)$ remains unchanged, but the effect of advertising under σ' does not vary with x.

5.2.1 Borrower Composition

Table 6: **Borrower Composition**. Results are obtained through simulation and rounded to the nearest dollar value.

Overall Borrowers	$E[\Delta NPV(r,x;\sigma)]$	-\$499
Should Wait	$E[\Delta NPV(r,x;\sigma)\|r^*_{ADL}(x) < r]$	-\$1282
Should Refinance	$E[\Delta NPV(r,x;\sigma)\|r^*_{ADL}(x) \geq r]$	\$5064
Ad Recipients in Data	$E[\Delta NPV(r,x;\sigma)\|a > 0]$	-\$58
Ad Non-recipients in Data	$E[\Delta NPV(r,x;\sigma)\|a = 0]$	-\$585

The first row of Table 6 shows that $E[\Delta NPV(r,x;\sigma)] = \int \Delta NPV(r,x;\sigma)dG(x) = -\$499$, so the average borrower would be approximately \$500 worse off if she decides to refinance. Thus refinancing is "harmful" to the average borrower, and advertising of refi loans could therefore be harmful. Whether advertising is beneficial or harmful depends on whether targeting and differential responsiveness dominate the effect of borrower composition.

Refi loans are likely to be similar to most advertised products for which $E[\Delta u(x)]$ is presumably also negative, so the average consumer would make a mistake if she buys the product. Unlike for refi loans, we cannot measure $E[\Delta u(x)]$ for most product. However, $E[\Delta u(x)]$ is likely to be very negative for products such as prescription drugs. Moreover, $E[\Delta u(x)]$ is likely somewhat negative for most products except for those that are purchased by the majority of consumers. Hence, to the extent that advertising affects only $\Delta\sigma$ and not $\Delta u(x)$, advertising for these products can only be beneficial if the effects of differential responsiveness dominate the effect of consumer composition.

Table 6 also shows the benefit from refinancing for those who should wait and those who should wait in rows two and three. While the average borrower who should wait would lose \$1282 by refinancing, the average borrower should should refinance would gain \$5064. Keys, Pope, and Pope

(2016) find that the median borrower who should refinance could gain $\$11,500$, which is significantly higher than our estimate. This difference is partly explained by the fact that they assume that borrowers who fail to refinance never refinance until the end of the mortgage, whereas we assume that their future refinancing behavior is governed by σ. Recall that "Should Wait" and "Should Refinance" are derived from the optimal refinancing policy by ADL. Therefore, $\Delta NPV(r,x;\sigma)$ is positive for some borrowers who "should wait". This is because $\Delta NPV(r,x;\sigma)$ does not assume that borrowers refinance optimally in the future. Instead, we assume that they follow the estimated refinancing policy. As the borrowers will not be able to exploit low interest rates in the future optimally, some borrower who should wait according to the ADL model, would be better off by refinancing today. For the same reason, all borrowers who should refinance according to ADL do indeed have positive $\Delta NPV(r,x;\sigma)$.

Lastly, Table 6 shows the benefit from refinancing for those who received advertising and those who did not in rows four and five. Borrowers who received advertising would lose on average \$58 while borrowers who did not receive advertising would lose \$585. This suggests that advertising is somewhat targeted. However, the gap between advertising recipients and nonrecipients (\$585 − \$58) is much smaller than the gap between those who should refinance and those who should wait (\$5064 + \$1282), so targeting could be much more beneficial for borrowers. In the next subsection we quantify the effect of targeting on borrower welfare in more detail.

5.2.2 Targeting

Table 7: **Targeting and Borrower Welfare**. Results are obtained through simulation and rounded to the nearest dollar value. E' is the expectation using the counterfactual advertising policy F'.

	Observed Advertising Policy F		**Evenly Distributed Advertising** F'	
All Borrowers	$E[\delta(r,x,a)]$	\$13	$E'[\delta(r,x,a)]$	\$11
Ad Non-recipients in the Data	$E[\delta(r,x,a)\vert a=0]$	\$0	$E'[\delta(r,x,a)\vert a=0]$	\$11
Ad Recipients in the Data	$E[\delta(r,x,a)\vert a>0]$	\$81	$E'[\delta(r,x,a)\vert a>0]$	\$12
Should Wait	$E[\delta(r,x,a)\vert r^*_{ADL}(x)<r]$	\$5	$E'[\delta(r,x,a)\vert r^*_{ADL}(x)<r]$	\$6
Should Refinance	$E[\delta(r,x,a)\vert r^*_{ADL}(x)\geq r]$	\$70	$E'[\delta(r,x,a)\vert r^*_{ADL}(x)\geq r]$	\$45

In Table 7 we compare the benefit of advertising under the observed advertising policy $F(a|x,r)$ with a counterfactual advertising policy $F'(a|x,r)$ such that F' is untargeted, i.e. does not vary with x and r and such that the average advertising intensity $\int adF(a|x,r)\,dG(x,r)$ remains unchanged. Hence, under F' the advertising exposure of every borrower is simply equal to the average exposure $\overline{a}=\int adF(a|x,r)\,dG(x,r)=0.23$. The main results in Table 7 are obtained by using our baseline responsiveness estimates in Table 3 to obtain $\Delta\sigma(a,r,x)=0.0159d_{ADL}(x,r)\times a+0.0250$. In Table

14 in the Appendix we present results that use the the dummy variables estimates from Column (1) in Table 5 to obtain $\Delta\sigma(a,r,x) = 0.0381 \times 1\{d_{ADL}(x,r) \geq 0\} \times a + 0.0042$.

The first column of Table 7 shows the benefits of advertising under the observed advertising policy F and the second column under F'. To avoid confusion we briefly clarify our notation. We denote the welfare of the average borrower under F' by $E'[\delta(r,x,a)]$. The welfare of the average borrower who received advertising under F, but now is exposed to F' is denoted by $E'[\delta(r,x,a)|a>0]$.

We find that the observed advertising policy F decreases the expected NPV for the average borrower by \$13. Hence, advertising helps borrowers on average even though the benefit of refinancing for the average borrower is -\$499, because the effects of targeting and differential responsiveness dominate the effect of borrower composition. As the benefit of refinancing for the average borrower who should refinance is more than \$5,000 the benefit of advertising could theoretically be much larger. This difference is due to two reasons. First, some borrowers are harmed by advertising, because $\Delta NPV(r,x;\sigma) < 0$. Second, even for the remaining borrowers the benefit of advertising is much smaller than $\Delta NPV(r,x;\sigma)$ because they receive only a small amount of advertising and respond only to a small fraction of ads they receive. The benefit of advertising is arguably large, however, in comparison to the marginal costs of sending refi advertising.

Under the counterfactual policy F' the benefit would decrease to \$11. Hence targeting increases borrower welfare by \$2 because advertising is somewhat targeted at borrowers who benefit from refinancing.[36] The benefit of \$13 under the observed advertising policy consists of a benefit of \$81 for advertising recipients and a benefit of \$0 for non-recipients as shown in rows (2) and (3). Under evenly distributed advertising the benefit of borrowers who do not receive advertising in the data would increase to \$11, whereas the benefit of borrowers who receive advertising in the data would decrease to \$12.

Rows (4) and (5) split the borrowers into those who should wait and those who should refinance. Under the observed advertising policy borrowers who should refinance gain \$70, whereas borrowers who should wait gain \$5. The benefit for borrowers who should wait is small but still positive, which is perhaps surprising. To understand this recall that $\Delta NPV(r,x;\sigma)$ is positive for borrowers who should wait with relatively high $d_{ADL}(x,r)$, because unlike the ADL rule $\Delta NPV(r,x;\sigma)$ does not assume that borrowers refinance optimally in the future, and that these borrowers are fairly responsive to advertising.[37] Under evenly distributed advertising the benefit of borrowers who should refinance would decrease substantially to \$45, whereas the benefit of borrowers who

[36] Table 12 in Appendix B is a targeting regression which shows that the number of advertisements a increases by 0.04 if $d_{ADL}(x,r)$ increases by one percentage point.

[37] In Table 14 in the Appendix, we use the dummy variable estimates from Column (1) in Table 5. In this specification there is no differential responsiveness within the group of borrowers who should wait and $E[\delta(r,x,a)|r^*_{ADL}(x) < r]$ is negative, but also small in magnitude.

should wait would increase slightly to \$6.

5.2.3 Differential Responsiveness

Table 8: **Differential Responsiveness and Borrower Welfare**. Results are obtained through simulation and rounded to the nearest dollar value in the left column and to \$0.1 in the right column. $E\left[\delta\left(r,x,a;\overline{\sigma}\right)\right]$is the expected borrower welfare if the estimated σ with differential responsiveness is replaced with the average responsiveness $\overline{\sigma}$.

	With Differential Responsiveness		**No Differential Responsiveness**	
All Borrowers	$E\left[\delta\left(r,x,a\right)\right]$	\$13	$E\left[\delta\left(r,x,a;\overline{\sigma}\right)\right]$	\$0.1
Ad Non-recipients in Data	$E\left[\delta\left(r,x,a\right)\lvert a=0\right]$	\$0	$E\left[\delta\left(r,x,a;\overline{\sigma}\right)\lvert a=0\right]$	\$0
Ad Recipients in Data	$E\left[\delta\left(r,x,a\right)\lvert a>0\right]$	\$81	$E\left[\delta\left(r,x,a;\overline{\sigma}\right)\lvert a>0\right]$	\$0.7
Should Wait	$E\left[\delta\left(r,x,a\right)\lvert r^*_{ADL}\left(x\right)<r\right]$	\$5	$E\left[\delta\left(r,x,a;\overline{\sigma}\right)\lvert r^*_{ADL}\left(x\right)<r\right]$	\$-0.5
Should Refinance	$E\left[\delta\left(r,x,a\right)\lvert r^*_{ADL}\left(x\right)\geq r\right]$	\$70	$E\left[\delta\left(r,x,a;\overline{\sigma}\right)\lvert r^*_{ADL}\left(x\right)\geq r\right]$	\$4.4

In Table 8 we try to understand to what extent the gains from advertising are due to differential responsiveness. The left column shows the benefit of advertising with differential responsiveness as estimated in section 4. The right column shows the benefit of advertising if all borrowers were equally responsive to advertising. We replace $\beta_1 d_{ADL}(x,r)\times a+\beta_2 a$ with the average responsiveness $\beta_1\overline{d_{ADL}(x,r)}\times a+\beta_2 a=0.0023a$ in σ, where $\overline{d_{ADL}(x,r)}=-1.49$ is the average distance to the optimal trigger rate. In Table 8 we use the baseline responsiveness estimates and in Table 15 in the Appendix we present results that use the the dummy variables estimates from Column (1) in Table 5. We denote the expected borrower welfare with average responsiveness by $E\left[\delta\left(r,x,a;\overline{\sigma}\right)\right]$. As the average responsiveness is fairly small, advertising has only a small effect in this scenario. Consequently, the average benefit decreases from \$13 to \$0.1.

Rows (2)-(5) on the left hand side of Table 8 are identical to Table 7. Rows (3) on the right hand side shows that the benefit of borrowers who receive advertising would decrease dramatically from \$81 to \$0.7 without differential responsiveness. Rows (4) and (5) on the right hand side show that "shutting down" differential responsiveness has a small negative effect on borrowers who should wait and a large negative effect on borrowers who should refinance.

In summary, we find that the observed advertising policy results in a positive benefit for the average borrower, because those with greater gains from refinancing are targeted by advertisers and more responsive to advertising. It is clear from Table 6, however, that more targeted advertising could increase borrower surplus considerably. Because borrowers who should refinance are more responsive, advertisers are likely to benefit from better targeting as well. In the next section we investigate the effects of better targeting in more detail.

5.3 Counterfactual With Better Targeting

Table 9: **Better Targeting and Borrower Welfare**. Results are obtained through simulation and rounded to the nearest dollar value. E'' is the expectation using the counterfactual advertising policy F''.

	Observed Advertising Policy		Redirected Ads	
All Borrowers	$E[\delta(r,x,a)]$	$13	$E''[\delta(r,x,a)]$	$45
Should Wait	$E[\delta(r,x,a)\,\vert r^*_{ADL}(x) < r]$	$5	$E''[\delta(r,x,a)\,\vert r^*_{ADL}(x) < r]$	$0
Should Refinance	$E[\delta(r,x,a)\,\vert r^*_{ADL}(x) \geq r]$	$70	$E''[\delta(r,x,a)\,\vert r^*_{ADL}(x) < r]$	$368

In Table 9 we assume that all of advertising is redirected to those who should refinance based on the ADL model, while keeping the total amount of advertising unchanged. We denote this advertising policy by F''. Under F'' all borrowers who should refinance receive $\overline{a}/\Pr(d_{ADL}(x,r) \geq 1) = 0.23/0.12 = 1.9$ refi mails and borrowers who should wait receive none. We denote the expected borrower welfare under F'' by $E''[\delta(r,x,a)]$. In Table 9 we use the baseline estimates and in Table 16 in the Appendix we use the dummy variable estimates from Column (1) in Table 5.

We find that the average benefit would increase from $13 to $45. The benefit for those who should refinance would increases from $70 to $368, whereas those who should wait no longer receive advertising and therefore obtain a benefit of $0.

Lenders would likely benefit from better targeting as well. Under the observed advertising policy, one piece of advertising increases the refinancing probability by 0.7 percentage points for those who received advertising. This is significantly higher than a 0.2 percentage point increase in refinancing probability under the counterfactual policy that evenly distributes advertising to all borrowers. Under the counterfactual policy that redirects all advertising to those who should refinance however, one piece of advertising increases the refinancing probability by 3.5 percentage points. Notice however, that if the spillovers of advertising are large, the advertising lenders might not actually benefit from improved targeting.

5.4 Discussion and Policy Implications

These findings raise the question why lenders don't improve targeting to reach more borrowers who should refinance as they are also more responsive. First, better targeting is expensive. By law, lenders are not allowed to have direct access to a borrower's credit file and can only purchase information about borrowers satisfying certain criteria from a credit bureau.[38] It is likely that the cost of acquiring such information might be too high, compared with benefits from better targeting.

[38] Publicly available records on house transactions can be used to estimate the remaining principal balance and the interest rate of a mortgage.

Second, if there is a positive spillover from advertising, then a lender might find it too costly to invest in better targeting of advertising. The positive spillover is likely present in this setting because a mortgage is essentially a homogeneous product. Hence, if refi advertising from a lender informs a borrower about the opportunity to save money by refinancing, the newly informed borrower might still refinance with a different lender. This positive spillover decreases the return to advertising from a lender's perspective. As a result, a lender might find it too costly to acquire better information about borrowers given the positive spillover.

Our findings suggest that policy makers should facilitate targeting of refi advertising to borrowers with greater gains from refinancing rather than restricting advertising for refi loans. For example, a policy that makes it easier for lenders to have access to a credit file from a credit bureau might lead to better targeting. Another possibility is for government-sponsored enterprises such as Freddie Mac and Fannie Mae to make more accessible information about borrowers, on their files, with potentially large gains from refinancing. Moreover, although there is a growing concern about privacy and collection of information about consumer, our findings suggest that limiting an advertiser's ability to target consumers can be costly.

6 Conclusion

This paper estimates the effect of advertising on refinancing mistakes and quantifies the resulting effect on borrower welfare. We find that refi advertising reduces the expected net present value of the average borrower by $13, even though the average borrower would lose approximately $500 by refinancing. In other words, the effects of differential responsiveness and targeting dominate the negative effect of borrower composition. An improved targeting policy that redirects all advertising would increase the gain in consumer welfare to $47 and lead to a fivefold increase in the responsiveness of the average ad recipient.

Our results highlight that firms do not only have an incentive to exploit the behavioral biases of consumers, but also to prevent consumer mistakes if they fail to buy products they need. The findings have implications for the regulation of advertising. First, advertising bans can be harmful for consumers, even if most consumers would be harmed by buying the product. Second, our results suggest that targeting of refi advertising should be facilitated as it would help borrowers and likely also advertisers. The benefits of such a policy, however, would have to be weighed against the privacy concerns of borrowers.

There are several avenues for future research. First, in this paper we did not consider the equilibrium effects of advertising. If advertising affects price, for example, such equilibrium effects could alter the effect of advertising on consumer welfare. Second, while our estimates incorporate the spillover effects of advertising, our data does not allow us to disentangle the spillover effects from the effect that accrues to the advertiser itself. Disentangling these two effects would allow us to better understand the incentives of advertisers (Sinkinson and Starc (2015), Shapiro (2016)).

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A ADL Trigger Rate

The optimal trigger rate is given by

$$r^*_{ADL} = \frac{1}{\psi}\left[\phi + W\left(-\exp\left(-\phi\right)\right)\right],$$

, where W is the principal branch of the Lambert $W-$function and

$$\begin{aligned}
\psi &= \frac{\sqrt{2\left(\rho+\lambda\right)}}{\sigma} \\
\phi &= 1+\psi\left(\rho+\lambda\right)\frac{\kappa/M}{\left(1-\tau\right)} \\
\lambda &= \mu+\frac{i_0}{\exp\left(i_0\Gamma\right)-1}+\pi \\
\kappa &= F+fM\left[1-\frac{\tau}{\theta+\rho+\pi}\left[\left(\frac{1-\exp\left(-N\left(\theta+\rho+\pi\right)\right)}{N}\right)\left(\frac{\rho+\pi}{\theta+\rho+\pi}\right)+\theta\right]\right]
\end{aligned}$$

Here, λ is the expected real rate of exogenous mortgage repayment and κ is the tax-adjusted refinancing cost. Table 10 summarizes the variables and parameters that enter the ADL threshold. The table also shows the parameter values suggested by ADL, which we use in our baseline estimates.

In robustness checks we explore the sensitivity of our findings to changes in the discount rate ρ and the standard deviation of the mortgage rate σ. The discount rate affects the trade-off between paying the upfront refinancing cost and future interest savings. For example consider a borrower with a remaining principal of $M = \$300,000$, a remaining term of $\Gamma = 25$ years and a mortgage rate of $i_0 = 0.06$. Under the standard value for $\rho = 0.05$ we obtain an optimal trigger rate of 0.0467 for this borrower. The threshold increases to 0.0474 for $\rho = 0.025$ and decreases to 0.0461 for $\rho = 0.075$. The standard deviation of the mortgage rate that the borrowers expect affects the option value of waiting. For example, under the standard value $\sigma = 0.0109$ the optimal trigger rate is 0.0467, which increases to 0.0501 for $\sigma = 0.0218$ and decreases to 0.0419 for $\sigma = 0.0054$.

Table 10: Parameters for the optimal trigger rate formula in Agarwal, Driscoll, and Laibson (2013).

Variable / Parameter		Value
ρ	Real Discount Rate	0.05
σ	Standard Deviation of Mortgage Rate	0.0109
M	Remaining Mortgage Principal	Data
τ	Marginal Tax Rate	0.28
μ	Annual Probability of Moving	0.1
i_0	Rate of Old Mortgage	Data
Γ	Remaining Mortgage Life	Data
π	Expected Average Inflation Rate	0.03
F	Cost of Refinancing	$2,000$
f	Number of Mortgage Points / 100	0.01
θ	Expected Arrival Rate of Full Deductability Event (move or subsequent refinancing)	$\mu+0.1$
N	Term of New Mortgage	$N=30$

B Additional Tables

Table 11: **First Stage for the Two Stage Least Squares Estimates in Table 4.** The first column shows the first stage for Table 4(1). The second column shows the first stage for the interaction term (Optimal Trigger - Market Rate) x Direct Mail Advertising for Table 4(2). The third column shows the first stage for Direct Mail Advertising for Table 4(2). County and quarter fixed effects are included.

	DMA (1)	(Optimal Trigger- Market Rate) x DMA (2)	DMA (3)
(Optimal Trigger - Market Rate) x DMA: Nonbanks		1.051^{***}	0.00373
		(0.0200)	(0.00778)
DMA: Nonbanks	1.060^{***}	0.00688	1.063^{***}
	(0.0183)	(0.0175)	(0.0175)
Optimal Trigger Rate - Market Rate (in %)	0.0128^{***}	0.0652^{***}	0.0124^{***}
	(0.00354)	(0.00869)	(0.00352)
Mortgage Inquiries (Past 3 Months)	-0.00394	0.0145	-0.00384
	(0.0140)	(0.0165)	(0.0140)
FICO Score	0.000241^{**}	-0.000192	0.000242^{**}
	(0.0000982)	(0.000156)	(0.0000985)
LTV Ratio	0.0373	-0.0511	0.0374
	(0.0258)	(0.0514)	(0.0258)
Income (in $1,000)	0.000132	-0.000337^{*}	0.000132
	(0.000157)	(0.000176)	(0.000157)
Age	-0.000424	0.00127^{*}	-0.000423
	(0.000396)	(0.000687)	(0.000396)
Observations	11396	11396	11396

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: **Targeting Estimates.** The dependent variable is the number direct mail advertisements for refinancing the borrower received in a month. County and quarter dummies are included. Standard errors are clustered at the county level.

Optimal Trigger Rate - Market Rate (in %)	0.0410***
	(0.00772)
Mortgage Inquiries (Past 3 Months)	-0.000848
	(0.0218)
FICO Score	-0.000327
	(0.000205)
LTV Ratio	0.113**
	(0.0528)
Income (in $1,000)	0.000518**
	(0.000234)
Age	0.000283
	(0.000626)
Constant	0.430**
	(0.194)
Observations	12301

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13: **Logit Estimates Used to Simulate NP$V_{refi}(r,x)$ and NP$V_{wait}(r,x)$.** As these estimates are used to predict future refinancing probabilities we do not include county and quarter fixed effects.

(Optimal Trigger - Market Rate) x (Direct Mail Adv.)	0.118***
	(0.0432)
Direct Mail Advertising (DMA)	0.154***
	(0.0477)
Optimal Trigger Rate - Market Rate (in %)	0.413***
	(0.0293)
Mortgage Inquiries (Past 3 Months)	0.718***
	(0.0749)
FICO Score	0.00495***
	(0.000813)
LTV Ratio	-0.0204
	(0.184)
Income (in $1,000)	0.00394***
	(0.000696)
Age	-0.00469*
	(0.00283)
Constant	-5.802***
	(0.662)
Observations	11599

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: **Targeting and Borrower Welfare**. These results use the dummy variable estimates from Column (1) in Table 5. E' is the expectation using the counterfactual advertising policy F'.

	Observed Advertising Policy F		**Evenly Distributed Advertising** F'	
All Borrowers	$E[\delta(r,x,a)]$	\$9	$E'[\delta(r,x,a)]$	\$5
Ad Non-recipients in Data	$E[\delta(r,x,a)\|a=0]$	\$0	$E'[\delta(r,x,a)\|a=0]$	\$4
Ad Recipients in Data	$E[\delta(r,x,a)\|a>0]$	\$57	$E'[\delta(r,x,a)\|a>0]$	\$8
Should Wait	$E[\delta(r,x,a)\|r^*_{ADL}(x)<r]$	\$-1	$E'[\delta(r,x,a)\|r^*_{ADL}(x)<r]$	\$-1
Should Refinance	$E[\delta(r,x,a)\|r^*_{ADL}(x)\geq r]$	\$82	$E'[\delta(r,x,a)\|r^*_{ADL}(x)\geq r]$	\$50

Table 15: **Differential Responsiveness and Borrower Welfare**. These results use the dummy variable estimates from Column (1) in Table 5. $E[\delta(r,x,a;\overline{\sigma})]$is the expected borrower welfare if the estimated σ with differential responsiveness is replaced with the average responsiveness $\overline{\sigma}$.

	With Differential Responsiveness		**No Differential Responsiveness**	
All Borrowers	$E[\delta(r,x,a)]$	\$9	$E[\delta(r,x,a;\overline{\sigma})]$	\$0.5
Ad Non-recipients in Data	$E[\delta(r,x,a)\,\vert a=0]$	\$0	$E[\delta(r,x,a;\overline{\sigma})\,\vert a=0]$	\$0
Ad Recipients in Data	$E[\delta(r,x,a)\,\vert a>0]$	\$57	$E[\delta(r,x,a;\overline{\sigma})\,\vert a>0]$	\$ 2.9
Should Wait	$E[\delta(r,x,a)\,\vert r^*_{ADL}(x)<r]$	\$-1	$E[\delta(r,x,a;\overline{\sigma})\,\vert r^*_{ADL}(x)<r]$	\$-1.9
Should Refinance	$E[\delta(r,x,a)\,\vert r^*_{ADL}(x)\geq r]$	\$82	$E[\delta(r,x,a;\overline{\sigma})\,\vert r^*_{ADL}(x)\geq r]$	\$17.6

Table 16: **Better Targeting and Borrower Welfare**. Results are obtained through simulation and rounded to the nearest dollar value. E'' is the expectation using the counterfactual advertising policy F''. These results use the dummy variable estimates from Column (1) in Table 5.

	Observed Advertising Policy		**Redirected Ads**	
All Borrowers	$E[\delta(r,x,a)]$	\$9	$E''[\delta(r,x,a)]$	\$50
Should Wait	$E[\delta(r,x,a)\,\vert r^*_{ADL}(x)<r]$	\$-1	$E''[\delta(r,x,a)\,\vert r^*_{ADL}(x)<r]$	\$0
Should Refinance	$E[\delta(r,x,a)\,\vert r^*_{ADL}(x)\geq r]$	\$82	$E''[\delta(r,x,a)\,\vert r^*_{ADL}(x)<r]$	\$404

C Differential Responsiveness Robustness Checks

Alternative Parameters for the Optimal Trigger Rate

For our baseline estimates we use the parameters for the optimal trigger suggested by Agarwal, Driscoll, and Laibson (2013) that are also used in Keys, Pope, and Pope (2016) and Agarwal, Rosen, and Yao (2015). Tables 17 shows results for alternative parameter values. The discount rate $\rho = 0.05$ is either increased to $\rho = 0.075$, which leads to a lower trigger rate, or decreased to $\rho = 0.025$, which leads to a higher trigger rate. Similarly, the annualized interest rate of the mortgage rate $\sigma = 0.01$ is either increased to $\sigma = 0.02$, which reduces the optimal trigger rate, or decreased to $\sigma = 0.005$, which increases the optimal trigger rate. These changes have only a minor impact on the estimates. Estimates for the main coefficient of interest β_1 range from 0.0142 to 0.0157.

Further Interaction Terms

Table 18 includes interactions of borrower characteristics such as age and income with direct mail advertising and the gap between the optimal trigger rate and the market mortgage rate in columns (2) and (3). Columns (4) and (5) include quadratic terms for direct mail advertising and the gap between the optimal trigger rate and the market mortgage rate. These changes have only a minor effect on the estimates of β_1 which range from 0.0149 to 0.0177. The estimates suggest that borrowers with higher income, higher FICO scores, higher LTV ratios and more previous mortgage inquiries are more responsive to $d_{ADL}(x,r)$, but no evidence that these variables affect the responsiveness to advertising.

Table 17: **Alternative Parameters for Optimal Trigger Rate.** Estimates for different combinations of the discount rate ρ and the annualized standard deviation of the mortgage rate σ. The discount rate equals $\rho = 0.05$ in columns (1), (4) and (7), $\rho = 0.025$ in columns (2), (5) and (8), and $\rho = 0.075$ in columns (3), (6) and (9). The standard deviation of the mortgage rate equals $\sigma = 0.0109$ in columns (1)-(3), $\sigma = 0.0054$ in columns (4)-(6) and lastly $\sigma = 0.0218$ in columns (7)-(9). County and quarter fixed effects are included. The standard errors are clustered at the county level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Optimal Trigger - Market Rate) x (Direct Mail Adv.)	0.0159***	0.0161***	0.0156***	0.0160***	0.0162***	0.0157***	0.0150***	0.0153***	0.0147***
	(0.00415)	(0.00416)	(0.00413)	(0.00406)	(0.00411)	(0.00402)	(0.00425)	(0.00425)	(0.00426)
Direct Mail Advertising (DMA)	0.0250***	0.0238***	0.0261***	0.0187***	0.0175***	0.0199***	0.0330***	0.0318***	0.0340***
	(0.00823)	(0.00794)	(0.00851)	(0.00693)	(0.00670)	(0.00716)	(0.0104)	(0.00999)	(0.0107)
Optimal Trigger Rate - Market Rate (in %)	0.0344***	0.0334***	0.0354***	0.0311***	0.0302***	0.0319***	0.0395***	0.0384***	0.0406***
	(0.00353)	(0.00347)	(0.00360)	(0.00327)	(0.00322)	(0.00331)	(0.00403)	(0.00391)	(0.00415)
Mortgage Inquiries (Past 3 Months)	0.0893***	0.0893***	0.0892***	0.0894***	0.0894***	0.0894***	0.0890***	0.0891***	0.0890***
	(0.0155)	(0.0155)	(0.0155)	(0.0155)	(0.0155)	(0.0155)	(0.0155)	(0.0154)	(0.0155)
FICO Score	0.000269***	0.000268***	0.000270***	0.000260***	0.000259***	0.000261***	0.000280***	0.000279***	0.000282***
	(0.0000707)	(0.0000707)	(0.0000707)	(0.0000708)	(0.0000707)	(0.0000708)	(0.0000703)	(0.0000704)	(0.0000703)
LTV Ratio	-0.0438**	-0.0384**	-0.0488**	-0.0328*	-0.0262	-0.0391**	-0.0567***	-0.0537***	-0.0593***
	(0.0198)	(0.0195)	(0.0201)	(0.0193)	(0.0190)	(0.0197)	(0.0205)	(0.0203)	(0.0207)
Income (in $1,000)	0.000334***	0.000344***	0.000325***	0.000354***	0.000364***	0.000344***	0.000301***	0.000310***	0.000292***
	(0.0000961)	(0.0000961)	(0.0000960)	(0.0000963)	(0.0000963)	(0.0000962)	(0.0000955)	(0.0000956)	(0.0000954)
Age	-0.000532	-0.000529	-0.000533	-0.000521	-0.000514	-0.000527	-0.000529	-0.000533	-0.000523
	(0.000329)	(0.000329)	(0.000329)	(0.000330)	(0.000330)	(0.000329)	(0.000328)	(0.000329)	(0.000328)
Constant	-0.111*	-0.118*	-0.103	-0.129**	-0.137**	-0.122*	-0.0791	-0.0865	-0.0723
	(0.0639)	(0.0637)	(0.0641)	(0.0634)	(0.0631)	(0.0636)	(0.0648)	(0.0646)	(0.0651)
Observations	11597	11597	11597	11597	11597	11597	11597	11597	11597

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 18: **Further Interactions and Quadratic Terms.** Column (1) are the baseline estimates. Columns (2) and (3) include interactions of borrower characteristics such as age and income with direct mail advertising and the gap between the optimal trigger rate and the market mortgage rate. Columns (4) and (5) include quadratic terms for direct mail advertising and the gap between the optimal trigger rate and the market mortgage rate. County and quarter dummies are included. Standard errors are clustered at the county level.

	(1)	(2)	(3)	(4)	(5)
(Optimal Trigger - Market Rate) x (Direct Mail Adv.)	0.0159***	0.0155***	0.0180***	0.0158***	0.0181***
	(0.00415)	(0.00423)	(0.00545)	(0.00411)	(0.00544)
Direct Mail Advertising (DMA)	0.0250***	0.0237	0.129	0.0253**	0.129
	(0.00823)	(0.0275)	(0.106)	(0.0108)	(0.107)
Optimal Trigger Rate - Market Rate (in %)	0.0344***	0.0388***	-0.194***	0.0354***	-0.193***
	(0.00353)	(0.0148)	(0.0408)	(0.00606)	(0.0407)
Mortgage Inquiries (Past 3 Months)	0.0893***	0.0883***	0.122***	0.0893***	0.122***
	(0.0155)	(0.0156)	(0.0245)	(0.0155)	(0.0245)
FICO Score	0.000269***	0.000274***	0.000634***	0.000272***	0.000630***
	(0.0000707)	(0.0000711)	(0.000106)	(0.0000702)	(0.000111)
LTV Ratio	-0.0438**	-0.0485**	0.0147	-0.0423**	0.0156
	(0.0198)	(0.0201)	(0.0329)	(0.0203)	(0.0338)
Income (in $1,000)	0.000334***	0.000618***	0.000595***	0.000335***	0.000596***
	(0.0000961)	(0.000143)	(0.000144)	(0.0000959)	(0.000144)
Age	-0.000532	-0.00102*	-0.000822	-0.000532	-0.000821
	(0.000329)	(0.000553)	(0.000556)	(0.000329)	(0.000557)
Income x Direct Mail Advertising		-0.000000114	-0.000000123		-0.000000123
		(0.000000122)	(0.000000122)		(0.000000122)
Income x (Optimal Trigger - Market Rate)		0.000000193***	0.000000183***		0.000000185***
		(5.74e-08)	(5.86e-08)		(5.82e-08)
Age x Direct Mail Advertising		0.000198	-0.00000325		-0.00000152
		(0.000455)	(0.000482)		(0.000482)
Age x (Optimal Trigger - Market Rate)		-0.000333	-0.000227		-0.000225
		(0.000220)	(0.000218)		(0.000219)
FICO Score x Direct Mail Advertising			-0.0000874		-0.0000858
			(0.000129)		(0.000128)
FICO Score x (Optimal Trigger - Market Rate)			0.000276***		0.000273***
			(0.0000472)		(0.0000488)
LTV x Direct Mail Advertising			-0.0466		-0.0468
			(0.0286)		(0.0287)
LTV x (Optimal Trigger - Market Rate)			0.0393***		0.0404**
			(0.0137)		(0.0160)
Mortgage Inquiries x Direct Mail Advertising			-0.00361		-0.00380
			(0.0296)		(0.0299)
Mortgage Inquiries x (Optimal Trigger - Market Rate)			0.0316***		0.0316***
			(0.0105)		(0.0105)
(Optimal Trigger Rate - Market Rate (in %))^2				0.000328	-0.000258
				(0.00129)	(0.00145)
DMA^2				-0.0000986	-0.000284
				(0.00237)	(0.00220)
Constant	-0.111*	-0.105	-0.420***	-0.113*	-0.417***
	(0.0639)	(0.0717)	(0.0955)	(0.0632)	(0.0972)
Observations	11597	11597	11597	11597	11597

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Heterogeneous Moving Propensity

The optimal trigger rate suggested by ADL assumes that borrowers move with a probability of 10% per year. In reality, the moving propensity varies across borrowers. Importantly, if borrowers foresee that they will move in the near future this can rationalize some of the behavior that appears to be a refi mistake. Conversely, if the borrowers know that their moving probability is lower than 10% this can explain some behavior that appears to be premature refinancing. If the moving propensity is not only known to the borrower, but also to the advertisers, and the advertisers target borrowers who are more likely to refinance, i.e. borrowers with low moving propensity, our findings could be explained by reverse causality.

To investigate this issue we predict heterogeneous moving propensities using borrower and loan characteristics. We consider not only moving but also "windfall prepayments" because they reduce the incentive to refinance in the same fashion as moving if they are anticipated by the borrower. We regress a dummy variable that captures moving and windfall prepayments on borrower and loan characteristics to predict heterogeneous moving propensities. We normalize the estimated moving propensities such that the mean is 10% to isolate the effect of heterogeneity rather than a shift of the mean.

Table 19 shows estimates using the estimated heterogeneous moving propensities. The estimates are similar to our baseline estimates which suggests that our finding is not driven by unobservable heterogeneous moving propensities.

Table 19: **Heterogeneous Moving/Windfall Propensity.** Here we use estimated heterogeneous probabilities for moving/windfall prepayments rather than a moving rate of $\mu = 0.1$ as assumed in the baseline specification and in Agarwal, Driscoll, and Laibson (2013). Table 20 shows the estimates used to predict the heterogeneous probabilities. In column (1) the heterogeneous probabilities are normalized such that the average moving rate is $\overline{\mu} = 0.1$. In column (2) we use the estimated probabilities without normalization. County and quarter dummies are included. Standard errors are clustered at the county level.

	(1)	(2)
(Optimal Trigger - Market Rate) x (Direct Mail Adv.)	0.0125***	0.0149***
	(0.00371)	(0.00389)
Direct Mail Advertising (DMA)	0.0221***	0.0214***
	(0.00787)	(0.00754)
Optimal Trigger Rate - Market Rate (in %)	0.0396***	0.0357***
	(0.00386)	(0.00354)
Mortgage Inquiries (Past 3 Months)	0.0889***	0.0890***
	(0.0155)	(0.0155)
FICO Score	0.000301***	0.000286***
	(0.0000706)	(0.0000708)
LTV Ratio	-0.117***	-0.0743***
	(0.0244)	(0.0214)
Income (in $1,000)	0.000356***	0.000366***
	(0.0000944)	(0.0000954)
Age	-0.000684**	-0.000625*
	(0.000328)	(0.000329)
Constant	-0.0825	-0.110*
	(0.0642)	(0.0638)
Observations	11597	11597

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 20: **Moving/Windfall Logit.** The dependent variable is an indicator that equals one if the borrower prepays the mortgage within the following year either because she moves or because she makes a "windfall payment", i.e. she prepays the mortgage ahead of schedule without refinancing or moving.

Rate of Current Mortgage (in %)	0.0535
	(0.0467)
Market FRM Rate (in %)	-0.382***
	(0.0800)
Loan Age	0.0000505
	(0.0000402)
Remaining Principal Balance (in $1,000)	-0.00000159*
	(0.000000815)
FICO Score	0.00197*
	(0.00106)
LTV Ratio	-3.302***
	(0.273)
Income (in $1,000)	0.00000275***
	(0.000000995)
Age	-0.00954**
	(0.00374)
Observations	11198

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 21: **Heterogeneous Interest Rate.** These estimates allow different borrowers to have access to different interest rates at a given point in time, instead of using the average market mortgage rate as the baseline specification. We estimate the borrower specific interest rate by regressing the interest rate on the old mortgage on the average market rate, the FICO score and the loan-to-value ratio — all at the time of origination. We interpret the residuals of this regression as a time-invariant borrower effect, which captures for example unobserved differences in default risk and differences in the cost of shopping for a better mortgage. We predict the borrower-specific interest rate with the updated market mortgage rate, FICO score, updated loan-to-value ratio and the borrower effect.
The dependent variable is a dummy that is equal to one if the borrower refinanced within three quarters. County and quarter fixed effects are included. Standard errors are clustered at the county level.

(Optimal Trigger - Market Rate) x (Direct Mail Adv.)		0.0171***
		(0.00458)
Direct Mail Advertising (DMA)	0.00846	0.0231***
	(0.00598)	(0.00847)
Optimal Trigger Rate - Market Rate (in %)	0.0470***	0.0436***
	(0.00407)	(0.00409)
Mortgage Inquiries (Past 3 Months)	0.0836***	0.0838***
	(0.0153)	(0.0153)
FICO Score	0.000191***	0.000192***
	(0.0000733)	(0.0000732)
LTV Ratio	-0.0488**	-0.0484**
	(0.0200)	(0.0201)
Income (in $1,000)	0.000307***	0.000312***
	(0.0000981)	(0.0000980)
Age	-0.000470	-0.000487
	(0.000339)	(0.000341)
Constant	-0.0347	-0.0392
	(0.0677)	(0.0675)
Observations	11334	11334

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 22: **Different Time Windows for Refinancing.** Columns (1)-(4) vary the time window used to define the dependent variable, column (1) considers only refis within 1 quarter, column (2) within 2 quarters etc. County and quarter dummies are included. Standard errors are clustered at the county level.

	(1) 1 Quarter	(2) 2 Quarters	(3) 3 Quarters	(4) 4 Quarters
(Optimal Trigger - Market Rate) x (Direct Mail Adv.)	0.00745***	0.0118***	0.0159***	0.0175***
	(0.00285)	(0.00383)	(0.00415)	(0.00476)
Direct Mail Advertising (DMA)	0.0149**	0.0213***	0.0250***	0.0254***
	(0.00582)	(0.00755)	(0.00823)	(0.00941)
Optimal Trigger Rate - Market Rate (in %)	0.0128***	0.0234***	0.0344***	0.0443***
	(0.00188)	(0.00283)	(0.00353)	(0.00418)
Mortgage Inquiries (Past 3 Months)	0.0828***	0.0863***	0.0893***	0.0926***
	(0.0131)	(0.0145)	(0.0155)	(0.0159)
FICO Score	0.000158***	0.000152***	0.000269***	0.000384***
	(0.0000434)	(0.0000580)	(0.0000707)	(0.0000849)
LTV Ratio	-0.0291***	-0.0340**	-0.0438**	-0.0190
	(0.0110)	(0.0170)	(0.0198)	(0.0249)
Income (in $1,000)	0.000122**	0.000182**	0.000334***	0.000446***
	(0.0000494)	(0.0000739)	(0.0000961)	(0.000117)
Age	-0.000142	-0.000196	-0.000532	-0.000496
	(0.000168)	(0.000243)	(0.000329)	(0.000405)
Constant	-0.0846**	-0.0554	-0.111*	-0.165**
	(0.0351)	(0.0508)	(0.0639)	(0.0766)
Observations	12031	11846	11597	11073

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$