Does Inequality Cause Financial Distress?
Evidence from Lottery Winners and Neighboring Bankruptcies

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ABSTRACT

We test the hypothesis that income inequality causes financial distress. To identify the effect of income inequality we examine lottery prizes of random dollar magnitudes, in the context of very small neighborhoods (13 households on average). We find that the larger the size of lottery prizes, the more subsequent bankruptcies among the winners' close neighbors. We also provide evidence on conspicuous consumption as a mechanism for this causal relationship. The larger the size of lottery prizes, the more likely that visible assets (house, car), but not invisible assets (cash, pension, securities), appear on the balance sheets of neighboring bankruptcy filers.

JEL Codes: D14, D31, K35

Keywords: income inequality, bankruptcy, conspicuous consumption, lottery, financial distress

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1. Introduction

It is a well-known stylized fact that income inequality (as measured for example by Piketty and Saez (2003 and updates)) peaked in the periods immediately prior to the financial crises of 1929 and 2008. Furthermore, as documented by Kumhof, Ranciere and Winant (2015), “the periods 1920-1929 and 1983-2008 both exhibited a large increase in the income share of high-income households, a large increase in debt leverage of low- and middle-income households, and an eventual financial and real crisis”(p.1217). These stylized facts have resulted in a number of papers, both macro (e.g. Kumhof et al, 2015) and micro (e.g. Georgarakos, Haliassos and Pasini, 2014 and Bertrand and Morse, 2015), attempting to link income inequality and individual financial distress. The basic hypothesis in many of these papers is that income inequality will cause poorer individuals to increase consumption in order to match the consumption of the rich (i.e. keeping up with the Joneses). Because this increased consumption of the poor will likely be financed by debt, this will eventually lead to financial distress for these poorer individuals.

While there is clearly extensive academic and policy interest in possible links between income inequality and financial distress, rigorous causal evidence is limited, largely because of the difficulty in identifying exogenous shifts in income inequality. It is usually inappropriate, for example, to simply consider changes in standard measures of income inequality (e.g. Gini Coefficients, top 1 % income share, etc.) as being exogenous. In this regard, Bertrand and Morse (2015) highlight the “the absence of an obvious instrument for the variation in top income levels across markets over time” (p. 1).

To the best of our knowledge, this paper provides the first micro based causal evidence on the link between income inequality and financial distress using exogenous shocks to inequality. The new research design proposed in this paper aims to capture cleanly exogenous shocks to income inequality by examining lottery wins by one individual within a very small neighborhood (in our case Canadian six digit postal codes containing 13 households on average). Our research design is based on the argument that the magnitude of a lottery prize by one member of a very small neighborhood will be an exogenous, and randomly sized shift in the income distribution of that specific neighborhood. This is because, on the date of the lottery win, the income of the lottery winner will increase by the random size of the lottery prize, while the income of her very close neighbors will remain unchanged.

Our measurement of financial distress exploits administrative data capturing the universe of bankruptcy filings in Canada, provided to us by the Canadian bankruptcy regulator, the Office of the Superintendent of Bankruptcy (OSB). We can observe the full annual count of every bankruptcy filing in every postal code in Canada. Our main unit of analysis is thus the six digit postal code (containing 13 households on average), where we can observe both the universe of lottery prizes won, as well as the universe of bankruptcy filings. Because we can use administrative data to observe the universe of bankruptcy filers, we are not required to measure outcomes (i.e. dependent variables) using post-lottery surveys, with their attendant problems of non-response bias, as undertaken by many other papers in the lottery literature.

The lottery games in our study all have random (rather than fixed) prize amounts, thus we can compare the impacts of large relative to small prizes. Because we can observe both the dollar magnitude of every lottery prize as well as the universe of every bankruptcy filing in that specific postal code, we can examine whether the random and exogenous magnitude of the lottery win has a causal impact on future bankruptcies of the very close neighbors of the lottery winner. Our research design thus tests the hypothesis that an exogenous shock to income inequality from a large lottery win in a neighborhood, will cause more subsequent bankruptcy filings from the winner's neighbors, compared to the number of neighboring bankruptcy filers following a small lottery win.

The key identifying assumption required to implement our research design is that the magnitude of a lottery win (conditional on there being a single win in the neighborhood) is exogenous, and is thus uncorrelated with any neighborhood level observable and unobservable characteristics. In terms of observable neighborhood characteristics we are able to use Canadian census level data to show that a large number of observable neighborhood level variables (e.g. neighborhood income, neighborhood Gini coefficient, etc.) are indeed uncorrelated with the magnitude of lottery wins in that neighborhood.

In order to control for neighborhood level unobservable variables we use a common recent methodology (e.g. Bayer, Ross and Topa, 2008; Linden and Rockoff, 2008; Campbell, Giglio and Pathak, 2011; Currie and Tekin, 2015; Currie, Davis, Greenstone and Walker, 2015; and many others), which has been used to "difference out" neighborhood level unobservables in contexts where neighborhood geographies are very small. This approach is based on the assumption that very close neighbors (in our case, bankruptcy filers within the same 13 household postal code of the lottery winner – which we label inner rings), and neighbors who are slightly further away (in our case, bankruptcy filers within an area of approximately 200 households or 0.2 square km of the lottery winner, but excluding the winner's postal code – which we label outer rings) are likely to share the same unobservable neighborhood attributes. We thus follow this literature in arguing that individuals in outer rings are good controls for individuals in inner rings, because they can be assumed to share the same unobservable neighborhood characteristics.

Following previous lottery based research (e.g. Hankins, Hoekstra, and Skiba, 2011), our main empirical specification is a cross sectional, event study type model, where the event date is the date of the lottery win within a neighborhood, and where we can examine the impact on neighboring bankruptcies in a wide variety of different event windows both before and after the event date.

Our main finding is that an increase in the dollar amount of a lottery prize significantly increases the number of subsequent bankruptcy filings by very close neighbors of the lottery winner (i.e. within the same six digit postal code). In the 0 to 2 year event window after the date of the lottery win, where there is a base of 0.45 bankruptcies per postcode over the three-year window, a one standard deviation increase in the log lottery prize in the postal code significantly increases the number of subsequent bankruptcy filings in that postcode by 8 %.

While these findings provide evidence of a causal link between the dollar magnitudes of lottery wins and subsequent neighborhood bankruptcies, they do not directly address the mechanism by which income inequality causes financial distress. In the second part of this paper, we examine how conspicuous consumption can act as a mechanism by which this causal relationship occurs. The conspicuous consumption argument is that income inequality will induce poorer neighbors to consume more visible (rather than invisible) commodities, in order to signal their abilities to "keep up with the Joneses" to their richer neighbors. This tendency can lead to additional and unsustainable borrowing among the relatively poor in order to finance this additional conspicuous consumption, which can eventually result in financial distress and bankruptcy. The testable implication of this conspicuous consumption argument is that it should be the consumption of goods that are visible to close neighbors, rather than the consumption of goods that are invisible to neighbors, that may lead to financial distress.

We are able to provide new evidence on the role of visible or conspicuous consumption in the link between income inequality and financial distress by exploiting the fact that our

Canadian bankruptcy data includes the full balance sheet of bankruptcy filers. These data allow us to observe the various categories of asset owned by each bankruptcy filer as of the date of their bankruptcy filing. The assets of bankruptcy filers we can observe include (1) conspicuous assets that are "visible" to neighbors such as cars, houses and motorcycles, as well as (2) assets that are invisible to neighbors, such as cash, securities and pension plans, etc.

We provide evidence that bankruptcy filers, who filed for bankruptcy following a larger lottery win of a close neighbor, are significantly more likely to own expensive visible assets (e.g. cars and houses) relative to the probability of owning these same visible assets owned by bankruptcy filers who filed for bankruptcy following smaller lottery wins of a close neighbor. A one standard deviation increase in the log lottery win leads to a 1.2% increase in neighboring bankruptcy filers owning an expensive home, and a 2% increase in neighboring bankruptcy filers owning an expensive car, on the date of the bankruptcy filing. In similar tests examining differences in the probability of holding invisible assets (e.g. cash, financial assets, pension), we find no significant differences between bankruptcy filers whose neighbors had relatively larger or smaller lottery wins.

2. Testable Hypotheses

This paper provides empirical evidence on two hypotheses. The first examines whether income inequality causes financial distress, while the second examines whether conspicuous consumption of visible (rather than invisible) goods is a mechanism by which this process operates. We discuss each in turn and how it relates to previous research.

2.1. Does Income Inequality Cause Financial Distress?

Our main hypothesis in this paper is that income inequality causes financial distress. Following the 2008 crisis, there has been considerable public and policy debate on whether income inequality causes financial distress (e.g. Rajan, 2010; Acemoglu, 2011; Becker, 2011; Stiglitz, 2013; Krugman, 2013; Cochrane, 2014; and many others). This literature proposes several mechanisms to link income inequality to financial duress. One mechanism proposed in Luttmer (2005) and Frank, Levine and Dijk (2010) works through the relative consumption of the individual and her neighbors. This specification of the utility function implies that the consumer derives displeasure when her consumption lags behind the consumption of relevant peers. Thus, keeping up with the Joneses behavior is generated by the model directly. Kumhof, Ranciere and Winant (2015) provide a slightly different mechanism by including a banking system in their model, through which richer households provide loans to poorer households to finance their increased consumption. This model endogenously generates excessive borrowing by the poor, which can trigger default (i.e. bankruptcy). Both these models imply that higher income inequality leads to higher consumption, more leverage and bankruptcy by the poor.

Bertrand and Morse (2015) and Frank, Levine and Dijk (2010) provide cross sectional evidence that income inequality in an area (US States or US Counties, respectively) is correlated with the number of household bankruptcy filings (as a measure of financial distress) in that area. Georgarakos, Haliassos and Pasini (2014) exploit survey data, which asks individuals to estimate the income levels of their peers. They show that individuals who believe themselves to be poorer than their peers will have higher levels of debt and greater likelihoods of financial distress. The link between inequality and financial distress has also been examined in various Macroeconomics papers, e.g. Bordo and Meissner (2012), Iacoviello (2008) and Krueger and Perri (2006).

While our paper is the first to examine the impact of exogenous income shocks on the *bankruptcy* filings of very close neighbors, a variety of papers have examined the impact of exogenous income shocks on the *consumption* choices of very close neighbors. The research design that is closest to ours is Kuhn, Kooreman, Soetevent and Kapteyn (2011), who explore the impact of lottery wins on the consumption choices of very close neighbors of the lottery winners, where their neighborhoods are defined by Dutch Postal Codes (with an average of 19 households). They find that a neighbor winning the lottery has a significant impact on consumption of non-lottery winning neighbors. Similarly, Angelucci and De Giorgi (2009) test the effect of exogenous government cash transfers on the consumption and debt choices of close neighbors. They also find that close neighbors of the transfer recipients increase consumption, in spite of not receiving the transfers themselves. Furthermore, they show that this increased consumption by the neighbors is financed by debt and gifts and by a reduction in savings.

Several other studies, however, have provided evidence that is not necessarily consistent with keeping up with the Joneses. Coibion, Gorodnichenko, Kudlyak and Mondragon (2014) find that the poor in high inequality areas have less debt than the poor in low inequality areas, which they ascribe to banks constraining the supply of credit to the poor in high inequality areas.

Bricker, Ramcharan and Krimmel (2014) provide evidence that is consistent with the rich attempting to “keep ahead of the Joneses”, rather than the poor “keeping up with the Joneses”.

Our study is also closely related to Hankins, Hoekstra, and Skiba (2011), who also exploit the exogenous variation in lottery prize size to examine the effect of exogenous income shocks on bankruptcy. However, these authors focus only on the impact of a lottery win on the bankruptcy of the lottery winner. By contrast, the focus of our paper is on the effect of lottery wins on the bankruptcy filings of very close non-winning neighbors.

In addition to the papers cited above, our use of lottery winner data forms part of a growing literature using lottery winnings, as a measure of exogenous income shocks, in a variety of contexts. Examples include Imbens, Rubin, and Sacerdote (2001) on labor supply, earnings, savings and consumption, Lindahl (2005) on health and mortality, Gardner and Oswald (2007), on psychological well-being, Apouey and Clark (2009) on physical and mental health, Hankins and Hoekstra (2011) on marriage and divorce, Bagues and Esteve-Volart (2013), on election outcomes, Briggs, Cesarini, Lindqvist and Ostling (2015) on stock market participation, Cesarini, Lindqvist, Ostling and Wallace (2015) on health and child development and Cesarini, Lindqvist, Notowidigdo and Ostling (2015) on household labor supply.

2.2. **Conspicuous Consumption as a Mechanism for Inequality to Cause Financial Distress**

The second hypothesis we empirically examine in this paper, is whether conspicuous consumption serves as a mechanism for keeping up with the Joneses. We test this by exploiting our ability to observe the full balance sheets of all bankruptcy filers including both visible assets (house, car, motorcycle) as well as invisible assets (cash, securities, and pension).

The hypothesis of conspicuous consumption (originating with authors such as Veblen, 1899; and Duesenberry, 1949) states that individuals will attempt to signal increased status by consuming high status goods that are more visible to their social reference groups. A variety of authors have specifically linked conspicuous consumption to income inequality (i.e. keeping up with the Joneses), where the relatively poor attempt to signal relative status by the consumption of more visible goods. Bertrand and Morse (2015) provide evidence that poorer individuals, in high inequality areas will be more likely to purchase more visible products. Examples of more visible products in their study (based on Heffetz, 2011) include shelter, cars and tobacco products, while examples of less visible expenses include health insurance, business services and interest paid.

Kuhn et al (2011) also provide evidence that higher income inequality leads to relatively poorer individuals purchasing more visible products. As described above, their identification strategy is similar to ours in that they examine the consumption of close neighbors of lottery winners. They find that a close neighbor winning the lottery has a very large and significant impact on the consumption of cars, and a less robust but still significant impact on the consumption of exterior home renovations. As noted by Kuhn et al (2011), cars and exterior home renovations are two of the most visible products that can be purchased.

3. Data

We use three main data sources for data on (1) Lotteries, (2) Bankruptcies and (3) Neighborhoods, which we discuss in turn. Full summary statistics of all data we use are reported in Table 1 for extensive margin data, and Table 7 for intensive margin data.

3.1. Lottery Data

All of the individual Provincial Governments in Canada have monopolies over official lotteries run in their jurisdictions. The Canadian Survey of Household Spending (Statistics Canada, 2013) shows that approximately two thirds of all adult Canadians purchase a provincial government run lottery ticket at least once a year. These data shows that purchases of government run lottery tickets are by far the most popular form of gambling undertaken by adult Canadians.

Our data include all lottery winners with more than \$1,000 in prizes, between April 1, 2004 and March 31, 2014 from a single Canadian province, provided to us by the provincial lottery organization (which under the terms of our Non-Disclosure Agreement, we are not able to divulge). The provincial lottery corporation does not keep track of lottery wins of less than \$1,000, thus it was unable to provide us with data on such wins (which is similar to many other lottery studies in the literature). The lottery corporation provided us with data on the winners' name (first name and last name), six digit postal code, dollar magnitude of lottery win, date of lottery win and type of lottery game for each win. Figure 1 provides a histogram of the dollar magnitudes of all (n=6,829) lottery prizes in our sample. Figure 1 shows that while there are a large number of smaller lottery wins of less than $3,000, there are a significant number of larger lottery wins, with a maximum of $150,000. As described above, these dollar magnitudes of lottery wins provide the key exogenous variation for our tests.

3.2. Bankruptcy Data

The Canadian bankruptcy regulator, the Office of the Superintendent of Bankruptcy, (OSB) has provided our individual level bankruptcy data. Because Canada has a single bankruptcy regulator (unlike the US), our data includes every bankruptcy filing in Canada.

There are two separate bankruptcy data bases, which provide the dependent variables for the two main empirical sections of this paper. The first data base provides complete data on the total annual counts of bankruptcy filings for each six digit postal code in Canada for every year between 1994 and 2013. We use these postal code level bankruptcy count data as our dependent variable to test the hypothesis that exogenous size of lottery wins impacts the count of subsequent bankruptcies among the winner's close neighbors. We label this specification "extensive margin" tests because it examines whether shocks to income inequality lead to additional counts of neighboring bankruptcies.

While our bankruptcy count data allow us to examine how many filers in a neighborhood filed for bankruptcy following neighboring lottery wins (i.e. the extensive margin), the OSB has also provided us with the full balance sheet of individual bankruptcy filers. These balance sheet data are required by law from every bankruptcy filer and are submitted to the OSB using OSB Form 79. These data are all publically available because a bankruptcy filing is by design a public legal document. These individual bankruptcy balance sheet data form the second of our two main bankruptcy data bases. We label this bankruptcy balance sheet data base, "intensive margin" data, because it reflects the characteristics of individual filers, rather than the counts of filers in a neighborhood. We use this individual level, balance sheet data to run intensive margin regressions examining how the size of lottery wins impact the individual balance sheet characteristics of neighboring bankruptcy filers.

3.3. **Neighborhood Data**

We use two separate neighborhood geographies to define the inner ring neighborhoods and outer ring neighborhoods described above. Our inner ring neighborhoods are Canadian six digit postal codes, which contain an average of 13 households. These areas are extremely small, often smaller than a city block in size. Single apartment buildings, for example, can have multiple six digit postal codes. Both our individual lottery winner data as well as our individual bankruptcy filer data contain postal code data for all individuals, thus our primary unit of analysis (i.e. inner ring) is defined by bankruptcy filers living in the lottery winner's six digit postal code.

Our second measure of neighborhood geography is called a Dissemination Area (or DA). These DAs contain approximately 200 households (i.e. the size a few city blocks) with an average size of approximately 0.2 square kilometers. Using a conversion process known as the Post Code Conversion File (PCCF) we can very accurately match Statistics Canada DA level geographies to the much smaller Canada Post six digit postal code geographies. Because we can observe both the six digit postal code, as well as the DA area of every lottery winner, we can define the outer ring neighborhood of the lottery winner by bankruptcy filers living in the area encompassing the winner's DA area excluding the winner's six digit postal code (which is defined as the inner ring).

An important advantage of our data is that the DA area is the smallest geographic area at which Statistics Canada provides data on observable neighborhood level characteristics from Census data. In particular, Statistics Canada provides DA level data on variables such as income, income distribution (which we use to compute Gini coefficients), unemployment, age, education, homeownership, gender, etc. We can thus include a large amount of data on observable neighborhood characteristics, measured for the exact geographic area (the 0.2 square kilometer DA) that constitutes the areas of our outer rings.

3.4. Relative Magnitude of Lottery Shocks to Income

An important element of all lottery-based studies is whether the magnitudes of the lottery prizes are salient relative to individual income levels. In Figure 1 we provide a histogram of the dollar magnitudes of all lottery wins in our sample, and in Figure 2 we provide kernel densities of Median DA Income at the DA level, taken from Canada Census data. These figures report data from the n=6,829 lottery wins and matched DAs in our main sample, described below. Figure 1 shows a large mass of small lottery prizes, as well as a very long tail of larger lottery prizes up to a maximum of $150,000. Figure 2 shows that the mean of the "Median DA Income" data across the DAs in our study is $31,000. In other words, the larger lottery prizes are clearly very salient relative to Median DA income, while the smaller prizes are somewhat inconsequential. (We describe the quartiles shown in Figure 2 below).

4. Research Design

Our identification strategy is to examine lottery wins, of exogenous and random dollar magnitudes. Our strategy is similar to much of the existing literature exploiting the random nature of lottery prizes (e.g. Imbens, Rubin and Sacerdote, 2001; Hankins, Hoekstra and Skiba, 2011; Cesarini et al, 2015; and others) in that we restrict our sample to lottery winners (in our case neighborhoods with a single lottery win), and compare large lottery wins to small lottery wins. We can thus avoid having to compare lottery winners to non-lottery winners, who may be systematically different because non-lottery winners may be non-lottery players.

4.1. Inclusion of Postal Codes with only a Single Lottery Win

Our research design restricts our sample to neighborhoods where there is only a single lottery win over the period of our data. The primary reason for this is based on the very long event windows in our study (5 years after the lottery win and 5 years before the lottery win for the placebo tests), and the difficulties in interpreting the impact of multiple events (i.e. multiple lottery wins in the postal code) within the same event window. By restricting our sample to only postal codes with a single lottery win over the period of our data, we have a clean test with a single exogenous shock, where the magnitude and date of the shock is random. The reason why we require such long event windows reflects the finding from the bankruptcy literature (e.g. Hankins, Hoekstra and Skiba, 2011, and many others) that the lags between an exogenous shock and a bankruptcy filing are long and variable. Our event window lengths are exactly the same as in Hankins, Hoekstra and Skiba (2011).

4.2. Removal of Fixed Prize Lotteries

We exclude all lottery wins where the lottery game has a fixed payout (e.g. "every winner wins $1,000"), and only include wins from games where the dollar amount of the lottery win is random (i.e. where the dollar magnitude of the win is determined by the size of the prize pool divided by the number of winning tickets). We do this because the central element of our identification strategy is that the dollar magnitude of the win should be randomly distributed. Our lottery winner data includes details of the exact nature of each type of lottery game, thus we are able to identify, and remove, all wins where there is a fixed rather than a random payout.

4.3. Removal of Very Large Winners

We also exclude from our sample all very large lottery wins of more than $150,000. Both Imbens et al (2001) as well as Hankins et al (2011) also exclude extremely large lottery winners from their samples (which can be many million dollars in magnitude), to reduce the possible impact of very large outliers. Our choice of $150,000 as the cut-off is exactly that of Hankins et al (2011). There are only 152 winners with prizes above $150,000, which is less than 2 percent of our main sample.

4.4. Removal of Winners who also file for Bankruptcy

Our research focusses on non-lottery winning neighbors of a lottery winner who subsequently file for bankruptcy, thus it is not appropriate to include in our data, those lottery winners who themselves filed for bankruptcy. Hence, we identify and exclude those lottery winners in a postal code who also filed for bankruptcy. There are 824 lottery winners in our sample who filed for bankruptcy at some stage in our sample (either before or after the lottery win), all of whom are excluded. To identify such individuals, we exploit the fact that our data include the first name, last name as well as six-digit postal code of all bankruptcy filers as well as the first name, last name and six-digit postal code of all lottery winners. Because of the very small size of postal codes (13 households on average), we argue that it is unlikely that two individuals with the same first and last names would live in the same postal code. We thus argue that our ability to match individuals based on first name, last name and six digit postal code is very high.

Even though our main focus in this paper is on the impact of lottery winners on the bankruptcy filings of *neighbors*, we also run a regression examining the impact of lottery winnings on their *own* bankruptcy filings, using data from the 824 winners who also filed for bankruptcy. However, we find no significant relationship in these own bankruptcy tests, possibly because of small sample size and low power issues.

4.5. Winners Subsequently Moving From the Neighborhood

An important issue raised by Hankins et al (2011) in their study of lottery winners who file for bankruptcy themselves, is the possibility that large lottery winners may be more likely to move out of the neighborhood compared to small lottery winners. As is the case with Hankins et al (2011), our data does not allow us to observe whether lottery winners subsequently move from the neighborhood.

Hankins et al (2011) provide some suggestive evidence on this issue by showing that there is no significant difference between large and small lottery winners appearing at the same address in telephone books in the years subsequent to the date of their lottery win. This indicates that, for wins of the magnitude of the larger lottery winners in their sample (max of US $150,000), there does not seem to be a systematic tendency for large winners to move location. (They argue that this evidence is only suggestive because telephone book listings of landline telephones are only partially reflective of all addresses).

This suggestive evidence is useful to us particularly because the magnitudes of the lottery wins in our study are very similar compared to the lottery win size magnitudes in the Hankins et al (2011) study. The maximum lottery win size in the Hankins et al (2011) study is US$ 150,000 (for Florida data from 1993 to 2002), while the maximum lottery win size in our study is C$ 150,000 (for Canadian data from 2003 to 2013). One of the reasons why both Hankins et al (2011) as well as our study drop very large winners of more than (C or US) $150,000 from our samples, is that these very large winners (often of many multiple millions of dollars) could be much more likely to move location following a lottery win, compared to the largest lottery winners in both our studies, with a maximum of only (C or US) $150,000.

In addition, an important econometric point is that in our neighbor-focused lottery study, *all* lottery winners appear in our data, irrespective of whether the lottery winner subsequently moves to another neighborhood. By comparison, in many winner-focused lottery studies, if a winner moves prior to the outcome of interest (e.g. bankruptcy), then that winner would not appear in the data. If, for example, a large winner in our study moved to a new neighborhood at some period after their win, we argue that they would at least have *some* influence on their original neighbors during the period from the date of their win to the date of their move. If there were a reduced impact on neighbors because large winners moved out of the neighborhood at some future date, this reduced influence would bias our estimated coefficients (which reflect the extent to which winners influence neighbors) towards zero. In other words, the significant coefficients that we report below are significant in spite of the possibility that some large winners may have moved from the neighborhood at some period of time after their win.

5. Justification for Identifying Assumptions

5.1. Neighborhood vs. Individual Unobservables

As described above, our study differs from the majority of lottery studies in that we examine the impact of lottery wins on the outcomes of *neighbors* rather than on the outcomes of the *winners* themselves. Because of our focus on the outcomes of neighbors rather than the outcomes of the winners themselves, we are required to address different issues related to identification and exogeneity. For example, the usual problem of omitted variable bias in studies examining the impact of lottery wins on the winners themselves, is that some individual level omitted variable may be correlated with both playing the lottery as well as the outcome of interest (e.g. bankruptcy).

It can be argued, however, that when examining the impact from one individual (the winner) on another individual (the close neighbor)), that individual level unobservables are not a primary concern. What remains a central concern, however, are neighborhood level observables and unobservables (i.e. where all individuals within a neighborhood, including the winner and the bankrupt neighbor(s), share the same observable or unobservable characteristics). In this section we describe how we control for both neighborhood observables as well as neighborhood unobservables.

5.2. Evidence for Neighborhood Observables

The central identifying assumption in the methodology comparing large and small lottery wins (e.g. Imbens, Rubin and Sacerdote, 2001; Hankins, Hoekstra and Skiba, 2011; Cesarini et al, 2015; and others) is that the size of the lottery win, conditional on winning, should be random. In other words, no observable and unobservable variables should be correlated with the size of the lottery win. In order to test this for neighborhood observables, we run essentially the same test as these authors above, by regressing the (log) size of the lottery win against a large number of observable variables. In our case, where we are interested in neighborhood level observables, we derive the list of observables from DA level census data (the full list of these census variables is provided in Table 1). This OLS regression results in an F-statistic for the joint significance DA level neighborhood variables of 0.95 with p-value of 0.5242, and an R squared = 0.0032. In other words, these results confirm that this large list of neighborhood observables have no predictive power on the dollar magnitude of the lottery win (conditional on their being a single lottery win in that neighborhood).

Figures 2 and 3, which show the median income in each DA, and the Gini coefficient for each DA, also provide additional graphic evidence of this lack of a relationship between DA observables and lottery win size. In both Figures 2 and 3, we plot the distribution of these variables across all DAs in our sample, for each of four lottery prize quartiles, based on the size of the lottery win. As can be seen in these Figures, the distributions of DA median income and Gini coefficient across the four lottery win size quartiles are essentially indistinguishable from each other, thus confirming visually, the statistical finding that there is no relationship between lottery win size and observable DA characteristics.

5.3. "Differencing Out" Neighborhood Unobservables

To control for neighborhood level unobservables we "difference out" bankruptcies of very close neighbors of the lottery winner (inner rings neighbors) from bankruptcies of neighbors who are slightly further away from the lottery winner (outer ring neighbors). Our approach closely follows the recent literature, which examines the causal effects of neighborhood events on their very close geographic neighbors. Examples include Linden and Rockoff (2008) (effects of sex offender location on neighborhood house prices), Currie, DellaVigna, Moretti, and Pathania (2010) (effects of fast food restaurants on neighboring obesity), Campbell, Giglio and Pathak (2011) (effects of foreclosure on neighborhood house prices), Pope and Pope (2015) (effects of Walmart opening on neighbourhood property prices), Currie and Tekin (2015) (effects of foreclosure on neighbourhood hospital visits), Currie, Davis, Greenstone and Walker 2015 (effects of toxic plants on neighboring infant mortality). Bayer, Ross and Topa (2008) have used this approach to examine whether close neighbors work for the same employer, and Grinblatt, Keloharju and Ikaheimo (2008) to examine whether close neighbors purchase the same cars.

In all of these papers cited above, the key assumption is that inner-ring and outer-ring neighbors share common unobservable attributes, because the size of both inner and outer rings is so small. Thus using outer ring neighbors as a control group for inner ring neighbors allows for the controlling for any unobservable selection into neighborhoods. For example, Linden and Rockoff (2008) argue that "individuals may choose neighborhoods with specific characteristics, but, within a fraction of a mile, the exact locations available at the time individuals seek to move into a neighborhood are arguably exogenous" (p. 1110). A similar argument can be made in terms of unobservable shocks to the neighborhood. Campbell, Giglio and Pathak (2011), for example, argue that "if there is a common shock in the neighborhood which generates an overall … trend within this microgeography, it will be captured by the difference between these two groups (inner rings and outer rings)." (p. 2125).

6. Results

As described above, we have two main hypotheses in this paper. The first examines whether exogenous lottery shocks impact the total counts of bankruptcies in that postal code neighborhood (which we label extensive margin tests). The second examines role of conspicuous consumption by testing the impact of exogenous lottery shocks on more or less visible balance sheet characteristics of individual bankruptcy filers (which we label intensive margin tests). We describe each in turn.

6.1. Extensive Margin Results: Neighborhood Bankruptcy Counts

All of our tests exploit the exogenous variation of the size of the lottery win, conditional on there being a single lottery win in the postal code over the course of our sample. For this reason the basic structure of our tests is an event study type cross-sectional specification, where the event of interest (the date of the lottery win) is set equal to t=0. This cross sectional specification, with event dates set relative to time t=0, is essentially the same as used by Hankins et al (2011). As in a standard cross sectional event-study type specification, we use various event windows before and after the lottery win to examine how the coefficient of interest changes over various time periods.

We initially estimate two separate regressions for each of the inner ring and outer ring neighborhoods, and we then combine both inner and outer rings together in a single model using interaction terms. We describe each in turn.

6.1.1. Inner Ring Model

Our basic inner ring model is as follows:

(1) $$Neighbor\_Bankruptcy\_Count_p = \beta_1 \ln\left(lottery\ win\ size\right)_p + \beta_2 (Controls)_d + \delta_p + \alpha_p + \varepsilon_p$$

where subscript p represents postal code of the winner, and subscript d represents the DA of the winner. As in the literature, (e.g. Imbens, Rubin and Sacerdote, 2001; Hankins, Hoekstra and Skiba, 2011; Cesarini et al, 2015), this is an event study type specification, where all events (lottery wins) are set to occur at time t=0. The dependent variable represents the total bankruptcy count in postal code p for a variety of different event windows, relative to t=0. Because our dependent variable is a count variable, we use the negative binomial specification. The key independent variable is the log of the lottery win size, occurring at time t=0. Given that this is a neighborhood level regression (our dependent variable is a count of total bankruptcies in a neighborhood) we are only able to include neighborhood rather than individual level controls. Time invariant neighborhood controls are measured at the DA neighborhood area d and are taken from Census data (a full list of these controls is provided in Table 1).

We also include lottery related fixed effects, capturing the calendar year of the lottery win (to capture business cycle variation), as well as a fixed effect for each of the different types of lottery game (Product) provided by the provincial lottery corporation. In terms of event window length, we closely follow Hankins et al (2011) in defining the various event windows we examine. As in Hankins et al (2011) we examine event windows after the date of the lottery win from 0 to 2 years, from 0 to 5 years and from 3 to 5 years. These long event windows reflect the well-known conclusion in the bankruptcy literature that the lag between an exogenous shock and the decision to file for bankruptcy is long and variable.

Results of this inner ring model are provided in Figure 4 (for event windows of individual years) and in Tables 2 and 3 (for event window of multiple years). Figure 4, which displays the estimated coefficient as well as the 95% confidence intervals for each individual year from t=-5 to t=5 (where the event date is year t=0), shows that the only significant year is year t = 2 with the coefficient of 0.0188. This coefficient estimate implies that one standard deviation increase in the log of the lottery prize increases neighbors' bankruptcies by 9.9 % relative to the mean number of bankruptcies per postal code in a single year of 0.148. In other words, these results imply that larger lottery wins will have a significant impact on bankruptcy filings of inner ring neighbors, relative to smaller lottery wins of inner ring neighbors, two years after the date of the lottery win.

Panel A of Tables 2 and 3 report similar results for event windows of groups of years rather than individual years. These results show that the only statistically significant group of years is the event window 0 to 2 years (0.047), which is significant at 5%. We can measure the economic magnitudes of this coefficient relative to the base amount of bankruptcies per postal code over the 0 to 2 year event window. As reported in Table 1, the base amount of bankruptcies per postal code over the 0 to 2 year event window is 0.456. Thus, a one standard deviation increase in the log of the lottery prize leads to an 8 % increase in neighborhood bankruptcies in the 0 to 2 year event window. Note that no coefficients are significant in Table 3, which consists of various event windows all of which occur before the event date. The positive sign on this coefficient is as expected, indicating that the larger the size of the lottery win the greater the number of neighboring bankruptcies.

Panels B to E of Tables 2 and 3 report estimates for the same equation, except that the sample is restricted based on various observable neighborhood characteristics. Panel B examines only DAs in Canada, which are classified by Statistics Canada as being urban, rather than rural neighborhoods (based on Statistics Canada's "Metropolitan Influence Zone" (MIZ) categorizations). These results show that only the event window from 0 to 2 years is significant, and that no event windows before the event date are significant. In other results (not reported) we find that no coefficients are significant for rural neighborhoods in Canada, based on Statistics Canada categorizations. These results imply that our estimated neighborhood effects are stronger for urban rather than rural neighbors.

Panel C of Tables 2 and 3 report estimates based on splitting the sample at the median DA Gini coefficient. Panel C reports results for DAs with above median income inequality. These results show significant coefficients for the 0 to 2 and 0 to 5 windows (both at 5%). Other results (not reported) show that no coefficients are significant for the sample of below median inequality DAs. These results are consistent with the argument that neighborhoods with high levels of pre-existing income-inequality (i.e. to the right of the distribution in Figure 3) will already have greater tendencies for "keeping up with the Joneses" type behavior prior to the lottery win, compared to low income-inequality neighborhoods. It could thus be argued that large lottery wins in already high inequality neighborhood will even further exacerbate these "keeping up with the Joneses" processes, thus leading to larger impacts on subsequent neighborhood bankruptcies, compared to similar lottery wins in neighborhoods with lower levels of pre-existing income inequality.

Panel D of Tables 2 and 3 splits the sample based on Statistics Canada measures of the prevalence in each DA of low-income individuals. We use the Low Income Cutoff (LICO) measure, which is the measure used by governments in a wide variety of programs targeting low-income individuals. Panel D shows results where the proportion of low-income individuals in a DA is above the median level across DAs. This result shows significant coefficients for the 0 to 2 (significant 1 %) and 0 to 5 event windows (significant at 5%). Other results (not reported) show that no coefficients are significant for DAs with below median number of low-income individuals. These results suggest that the neighborhood spillover processes we observe are stronger in low income rather than high-income neighborhoods.

Panel E of Tables 2 and 3 split the sample based on postal codes where there are multiple postal codes at the exact same location (i.e. latitude and longitude measure). The existence of multiple postal codes at a single location is indicative of apartment buildings, or other multi-family type buildings. The results in Panel E indicate that when restricting the sample to areas containing such multi-family buildings, that the results are significant for the 0 to 2 and 0 to 5 event windows. In other results (not reported) there are no significant coefficients when the sample is restricted to only single postal codes at each location (i.e. single family buildings). In other words, we can conclude that the neighborhood spillover effects we observe are more prevalent in neighborhoods containing multi-family type buildings compared to neighborhoods containing single-family type buildings.

We can also compare the magnitudes of the coefficients across panels A to E in Figure 2, especially for the 0 to 2 event windows. For example, we find that as population density increases (from rural (insignificant coefficients not reported) to urban (panel B) to multi-family (panel E)) so the impact of neighborhood spillovers increases in magnitude.

6.1.2. Outer Ring Model

While Tables 2 and 3 report results of the inner ring model, Table 4 reports results for the same model, except that the dependent variable is a measure of bankruptcy counts in the outer ring. Because the outer ring neighborhoods (winner's DA excluding winner's postal code) are much larger than inner ring neighborhoods (winner's postal code), we normalize these neighborhood bankruptcy counts by dividing the number of bankruptcies in the outer ring by the number of postal codes in the outer ring (i.e. the number of postal codes in the DA less 1). Because of this normalization, our dependent variable is a continuous variable, thus we use OLS in these specifications.

Results in Table 4 indicate that no coefficients of interest are significant for event windows after the event date. In addition, when we run these models for individual years from t-5 to t+5 (not reported) we also find no significant coefficients. In other words, while we can conclude from the section above that there is evidence of significant neighborhood spillovers within inner ring neighbors, we find no significant evidence of neighborhood spillovers for outer ring neighbors.

6.1.3. Outer Rings as controls for Inner Rings

While the previous sections separately estimated inner ring and outer ring models, this section follows the recent literature who control for neighborhood level unobservables by using outer ring neighbors as controls for inner ring neighbors, based on the assumption that because inner and outer rings are so small that they share the same unobservables.

Our specification in this regard closely follows Currie et al (2015), who also differences out "far" neighbors from "near" neighbors.

(2)

$$Neighbor\_Bankruptcy\_Count_{pr} =$$
$$\beta_1 \ln\big(lottery\ win\ size\big)_p + \beta_2 Near_r + \beta_3(\ln\big(lottery\ win\ size\big)_p \times Near_r + \beta_4 (Controls)_d +$$
$$\delta_p + \alpha_p + \beta_5 (Controls)_d \times Near_r + (\delta_p + \alpha_p) \times Near_r + \varepsilon_{pr}$$

We define our dependent variable (bankruptcy counts per annum in the neighborhood) in a way that is essentially the same as Currie et al (2015). For each lottery win observation (subscript p), we define two separate observations of neighborhood bankruptcy counts (denoted with subscript r). The first is the annual number of bankruptcies filed by inner-ring neighbors (within the winners postal code) and the second is the annual number of bankruptcies filed by outer-ring neighbors (within the winner's DA, excluding the winner's postal code) divided by the number of postal codes within DA minus 1.

The main new element of this model is the indicator variable "Near" which is a dummy variable equal to 1 for bankruptcies of inner ring neighbors (i.e. within the winner's postal code), and equal to 0 for bankruptcies of outer ring neighbors (i.e. within the winner's DA excluding the winner's postal code). Thus, following Currie et al (2015) when the independent variable Near is coded as 1, the dependent variable measures bankruptcy counts for inner ring neighbors, while when Near is coded as 0, the dependent variable captures bankruptcy counts of outer ring neighbors. Coefficient β_3 is the main coefficient of interest in this specification in that it captures the interaction of ln(lottery win size) and Near. This coefficient captures the impact of lottery prize size on bankruptcies of near neighbors, relative to the impact of lottery wins on bankruptcies of far neighbors.

As in our inner and outer ring models above, this model also includes a large number of DA level neighborhood characteristics as observable controls, which are listed in Table 1. As in the models above we also include Year of win fixed effects, and Fixed Effects for each of the different kinds of lottery games in our study. In addition, however, this model also includes a large number of separate interaction terms of the Near variable with (1) each of the observable DA characteristics variables, (2) each of the Year FE, and (3) each of the lottery game types FE.

Our results for the β_3 coefficient (interacting win size with Near) are reported in Figure 5 (individual years), Table 5 (for event windows after lottery win) and Table 6 (for event windows before lottery win). Our main findings are that these results in Figure 5, Tables 5 and 6, where inner ring unobservables are controlled for by outer ring unobservables, are very similar to the results for the inner ring only specifications in Figure 4, Tables 2 and 3. In the case of event windows before lottery win, no coefficient in Table 6 is significant. Furthermore, all of the significant coefficients in Table 5 are also the same significant variables reported in Table 2. The magnitudes of the coefficients in Table 5 are slightly higher than the magnitude of the coefficients in Table 2, which indicates the impact of including outer ring neighbors within the same specification.

Our main conclusion from showing that the inner ring only results (Table 2) are very similar to the results where inner rings are controlled for by outer rings (Table 5), is that neighborhood level unobservables do not appear to be a significant factor in explaining our inner ring results.

6.2. **Intensive Margin Tests: Visible or Invisible Assets**

The intensive margin tests in this section are all at the level of the individual bankruptcy filer (i), rather than at the aggregate neighborhood level, as in the extensive margin tests above. Thus, while the dependent variable in our extensive margin tests, above, are counts of neighboring bankruptcies, the dependent variables in our intensive margin tests are balance sheet characteristics of those individual neighbors who do file for bankruptcy following a lottery win of a neighbor. In particular, the characteristics we examine relate to various visible and invisible assets as reported by bankruptcy filers to the OSB on the date of their bankruptcy filing. Thus our intensive margin tests examine all individual bankruptcy filers in the neighborhoods of lottery winners, and compare whether bankruptcy balance sheet characteristics of these individual bankruptcy filers differ between larger or smaller lottery wins in their postal codes.

Our intensive margin specification is as follows:

$$(3) \quad Bankrupt\_Asset_i = \beta_1 \ln\big(lottery\ win\ size\big)_i + \beta_2(Controls)_i + \delta_i + \alpha_i + \varepsilon_i$$

The key independent variable (log of lottery win size) is identical to that used in the extensive margin tests above. Because the intensive margin specification is at the level of the individual (non-lottery winning, bankruptcy-filing neighbor) we can also include individual level controls of the bankruptcy filing neighbor, in addition to the neighborhood controls used above. Details of these controls are provided in Table 2. Similarly, because these tests are at the level of the individual bankruptcy filer (i), we can also include dummies for each of the 17 different "reasons for financial distress" given by filers when they file, as reported by the OSB. These reasons are also described in Table 7. As in the extensive margin specification above, lottery specific fixed effects (i.e. lottery product and lottery winning year fixed effects) are also included.

Because our focus in these intensive margin tests is the individual neighbor, rather than aggregate counts within a neighborhood, we do not difference out bankruptcy counts of inner-ring neighbors from bankruptcy counts of outer ring neighbors. When differencing out inner ring from outer ring neighbors (as above), it is necessary to create aggregates or averages of inner and outer rings, thus losing data on individual level heterogeneity. Aggregation to the neighborhood level would also preclude us from including the large number of individual level observables as controls in these individual level specifications. Furthermore, given our conclusion above that neighborhood level unobservables where not of importance in the extensive margin models, it is unlikely that they will be of importance in these intensive margin models.

We can examine a variety of different specifications to categorize the various balance sheet measures of the different assets at bankruptcy of neighboring bankruptcy filers. Summary statistics for all of the various bankruptcy balance sheet assets are reported in Table 7. From this table it can be seen that for many of these assets across many of these filers there was a zero reported in the bankruptcy filing (i.e. that bankruptcy filer did not own that asset as at the date of the filing). For this reason, in our chosen specification, we classify the various assets owned by these bankruptcy filers as dummy variables, indicating whether or not they owned that asset, rather than a continuous dollar measure.

For two particular assets however (houses and cars), we do have enough variation in the data to also provide additional classifications for “expensive houses” and “expensive cars”. We do this in order to test the specific hypothesis that conspicuous consumption operates specifically through “expensive house” and “expensive cars”, rather than simply through all houses and cars. In particular, we classify expensive cars as cars over \$10,000 and expensive houses as houses over \$350,000 (assets lower than these cut-off values, including zeroes, are coded as 0). Approximately 22 % of the samples of bankruptcy filers have car assets greater than \$10,000, and approximately 8 % of the bankruptcy filers in the sample have housing assets greater than \$350,000. We use logit specifications to model these binary dependent variables.

It is important to note, however, that because our bankruptcy balance sheet data only reports assets owned by the bankruptcy filer as of the date of the bankruptcy filing, we are not able to observe the date at which any asset was purchased. This means that we are not able, for example, to examine whether the purchase of any asset occurred before or after the date of the neighbor’s lottery win. What we can observe, however, is that these visible assets (car, house) are durable assets, which the debtor retains ownership of, even after the lottery win of a neighbor, and does not dispose of in order to reduce debt. In other words, we are able to use this bankruptcy balance sheet data to compare the relative amount of visible and durable assets, which provide consumption every period owned, across bankruptcy filers caused by neighborhood lottery wins of different amounts. These intensive margin tests thus capture the preferences across bankruptcy filers for more or less visible and durable assets and consumption as reflected in filers’ balance sheets on the date of their bankruptcy filing.

We report results for our intensive margin balance sheet tests in Table 8 and Figure 6. In each cell we report the marginal effect of the lottery prize size in that neighborhood on various balance sheet amounts reported by non-winning bankruptcy filers in that neighborhood. In this Table, we only report a single coefficient (on log lottery win size) from each regression. Full results are available upon request.

Our main result in Table 8 and Figure 6 is that we find significant coefficients for Expensive Cars (defined as cars over $10,000), Expensive Houses (defined as houses over $350,000) and motorcycles. These coefficients are significant in the 0 to 2 year event window. In other words, these results are consistent with the hypothesis that the larger the lottery prize of a neighbor, the greater the probability that the neighboring non-winning bankruptcy filer will hold relatively expensive visible assets (expensive houses and expensive cars). When examining invisible assets such as cash, furniture, pensions and securities, we do not find any significant coefficients – either for the continuous or binary asset size measures. In no case do we find any significant coefficient for the tests examining bankruptcy filings before the lottery win (Table 9). These results are consistent with the causal nature of the lottery prize size as an exogenous neighborhood income inequality shock.

In terms of economic magnitudes, the coefficient for the 0 to 2 year event window (0.0128) for expensive houses implies that a one standard deviation increase in log lottery win size causes a 1.2% increase in the probability of a neighboring lottery winner owning an expensive house on the date of the bankruptcy filing. Similarly, the coefficient on expensive cars (0.0207) for the 0 to 2 event window implies that a one standard deviation increase in log lottery win size leads to a 2% increase in neighboring bankruptcy filers owning expensive cars on the date they file for bankruptcy.

In summary, our main results show that when we consider jointly our extensive (count) data results as well as our intensive (balance sheet) data results, we can conclude that the larger the size of a neighborhood lottery win: (1) the greater the number of subsequent neighborhood bankruptcies (extensive margin), and (2) the greater the amount of visible assets owned by those neighboring bankruptcy filers on the date of their bankruptcy (intensive margin).

7. Conclusion

This paper provides causal evidence that exogenous shocks to income inequality cause financial distress. Our identification strategy is to examine how lottery prizes of random magnitudes impact bankruptcy filings by very close neighbors of the lottery winner. Using Canadian administrative data, we can observe the universe of lottery winners and the universe of bankruptcy filers, within Canadian six digit postal codes, containing on average 13 households. We find that the magnitude of a lottery win causes a significant increase in bankruptcy filings within the winner's postal code in the 0 to 2 year event windows as well as in the 2nd year (as a single year) event window. Using bankruptcy balance sheet data, we also provide evidence that conspicuous consumption plays a role in this causal relationship. We find that the larger the magnitude of a lottery prize, the larger the probability that close neighbors of the winner who file for bankruptcy will own expensive houses and expensive cars at the date that they file for bankruptcy.

Our new causal evidence is important both in terms of explaining micro based relationships between individuals and their very close neighbors, but also because of links to macro based debates linking inequality and financial distress. These macro debates relate to the stylized facts (e.g. Piketty and Saez, 2003 and updates) that various measures of income inequality peaked in the periods before the financial crises of 1929 and 2008. While we do not provide any macro based evidence, our results do show that at the very micro household and neighborhood level, income inequality does indeed cause financial distress.

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Figure 1. The Distribution of Lottery Prizes among Postal Codes with Single Winners with less than $150,000 in Winnings

Figure 2. The distribution of DA median income by lottery amount

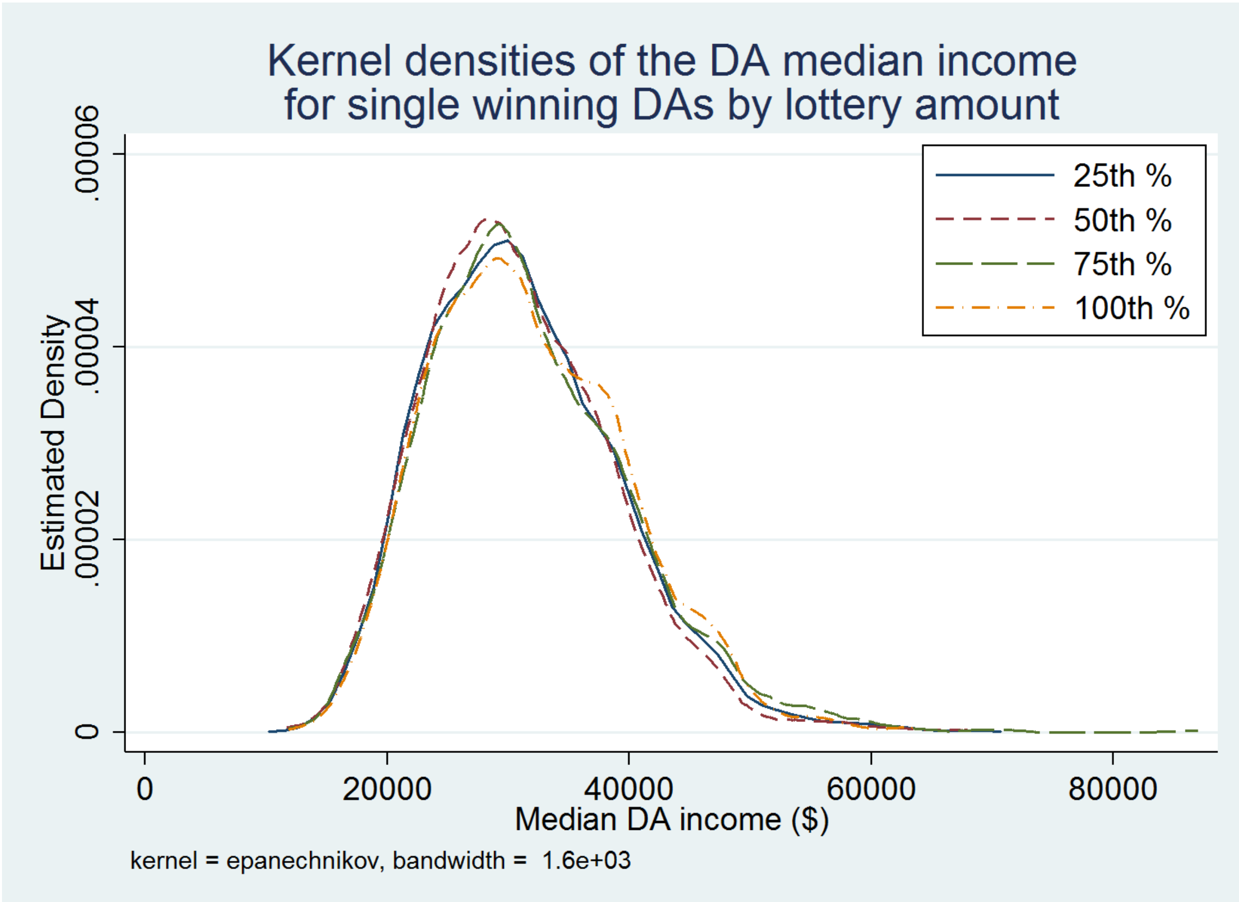


Figure 3. The distribution of pre-existing income inequality by lottery amount

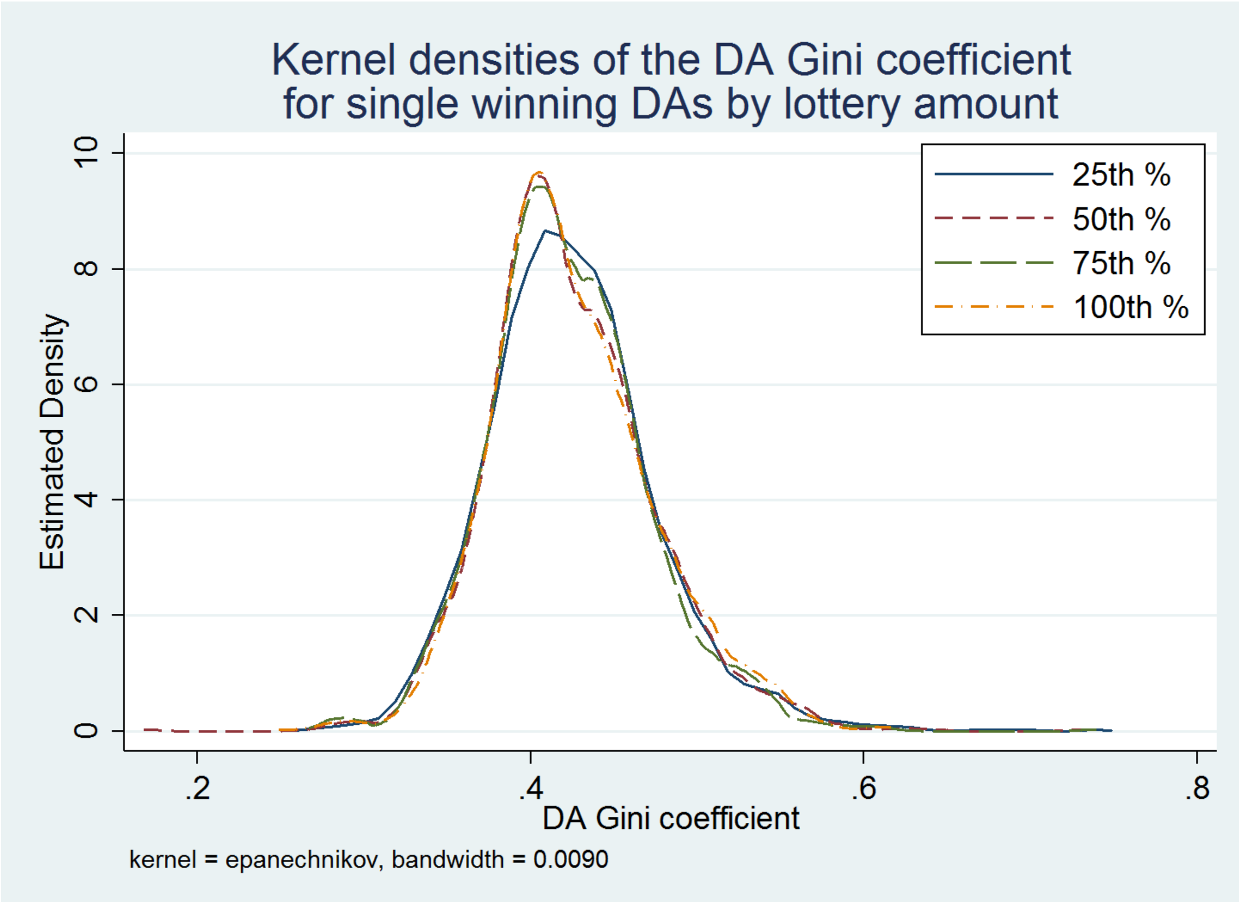
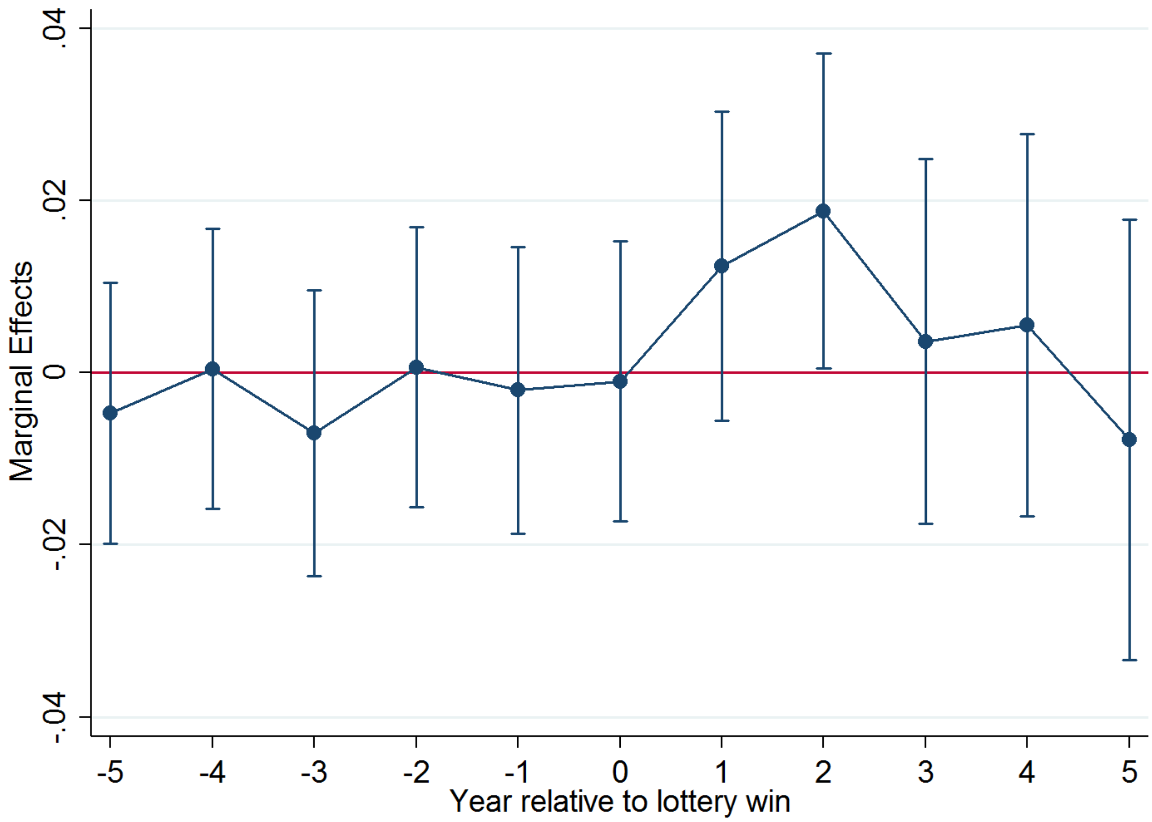
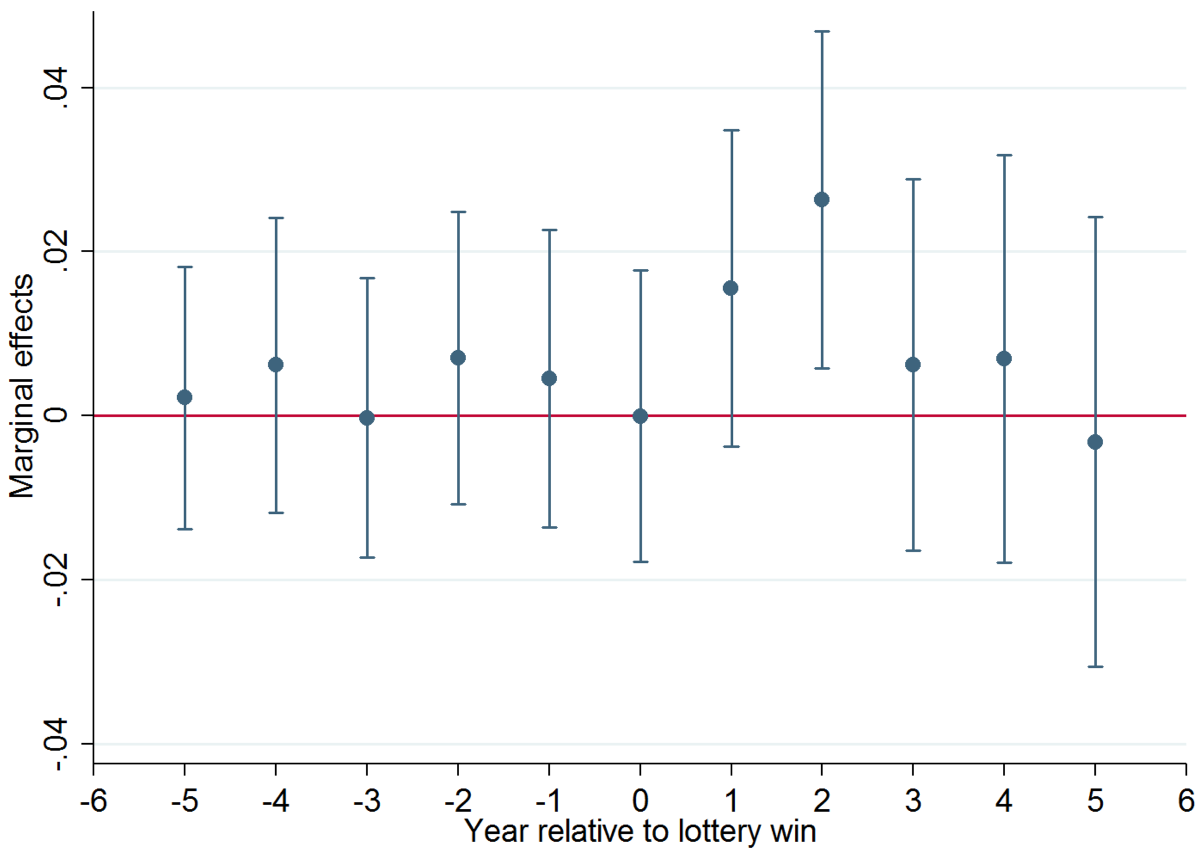


Figure 4. The effect of the size of lottery winning on counts of neighbors' bankruptcies over time (inner rings)



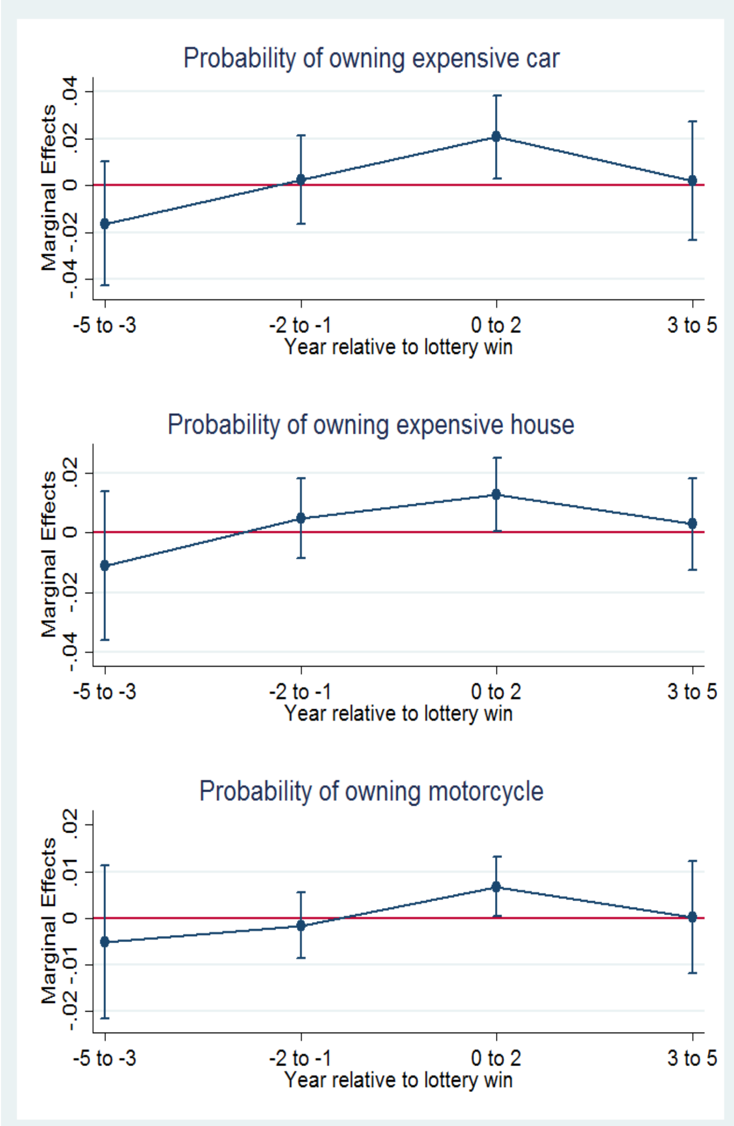
Notes: This figure shows estimated coefficients on the log of lottery win as dots and 95 % confidence intervals as bands. All coefficients are marginal effects from separate Negative Binomial regressions with the number of postal code bankruptcies from winners' neighbors as the dependent variable. All specifications include lottery product and winning year fixed effects. Control variables consist of DA level Gini coefficient, median income, population density, region's influence on urban core, DA numerical literacy, unemployment rate, family breakdowns, homeownership, age and gender distributions, and education levels. We consider postal codes with one prize during our study period, with randomly sized prizes of above $1,000 and below $150,000.

Figure 5. The effect of the size of lottery winning on counts of neighbors' bankruptcies over time, controlling for neighborhood unobservables (inner rings – outer rings)



Notes: This figure shows estimated coefficients on the log of lottery win interacted with being in the inner ring as dots and 95 % confidence intervals as bands. All coefficients are marginal effects from separate OLS regressions with the number of postal code or outer ring bankruptcies from winners' neighbors as the dependent variable. All specifications include lottery product and winning year fixed effects. Control variables consist of DA level Gini coefficient, median income, population density, region's influence on urban core, DA numerical literacy, unemployment rate, family breakdowns, homeownership, age and gender distributions, and education levels. We consider postal codes with one prize during our study period, with randomly sized prizes of above $1,000 and below $150,000.

Figure 6. The effect of the size of lottery winning on conspicuous asset ownership among bankruptcy filers within winners' postal codes over time (intensive margins)



Notes: Definitions of Expensive House and Expensive Cars in the text. All tests are Logit tests because all dependent variables are categorical as to whether an asset is present in the bankruptcy balance sheet or not. This figure shows estimated coefficients on the log of lottery win as dots and 95 % confidence intervals as bands. All coefficients are marginal effects from separate Logit regressions. All specifications include lottery product and winning year fixed effects. Control variables are described in Table 7 and the text. We consider postal codes with one prize during our study period, with randomly sized prizes of above $1,000 and below $150,000. These coefficients imply that the probability of owning conspicuous consumption assets in bankruptcy increases in lottery size for filers in years 0 to 2 after neighbor's lottery winning.

Table 1. Summary Statistic of Winning Postal Code Data (Extensive Margins)

Variable	Obs.	Mean	Std. Dev.
Winning amount ($)	6829	4778.8	12663.4
Log of winning amount	6829	7.859	0.778
Winning year	6829	2009.5	2.6
Bankruptcy rate relative to the winning time, years:			
0 to 2	4932	0.456	0.972
3 to 5	2372	0.417	0.914
0 to 5	2372	0.811	1.489
-1 to - 2	6829	0.298	0.733
-3 to - 5	6829	0.405	0.937
-1 to - 5	6829	0.703	1.364
DA Gini coefficient	6829	0.424	0.049
Median income ($)	6829	31448.3	8053.7
Population density (person per sq. km)	6829	2558.9	2307.0
Region type (1 to 8 score)	6829	1.575	1.236
Unemployment rate (%)	6829	4.096	3.370
Numerical literacy score (between 100 and 500)	6829	277.5	11.3
Divorced (proportion of DA population)	6829	0.078	0.032
Separated (proportion of DA population)	6829	0.028	0.015
Widowed (proportion of DA population)	6829	0.046	0.044
Graduate (DA) (proportion of DA population)	6829	0.233	0.069
University (DA) (proportion of DA population)	6829	0.122	0.058
College (DA) (proportion of DA population)	6829	0.208	0.064
Apprenticeship (proportion of DA population)	6829	0.190	0.105
High school (proportion of DA population)	6829	0.063	0.062
Homeownership	6829	0.386	0.079
Male	6829	0.498	0.028
Aged between 20 and 39	6829	0.301	0.098
Aged between 40 and 64	6829	0.335	0.068
Aged over 65	6829	0.109	0.087

Table 2. The Effect of Lottery Winning on Winners' Neighbors (Extensive Margin)

Event Window (years)	0 to 2	3 to 5	0 to 5
Panel A. Whole sample			
Log of winning amount	0.0470**	0.0151	0.0630
	(0.0191)	(0.0250)	(0.0393)
Number of observations	4,932	2,372	2,372
Panel B. Urban, high density neighborhoods			
Log of winning amount	0.0459**	0.00914	0.0452
	(0.0207)	(0.0272)	(0.0415)
Number of observations	3,738	1,772	1,772
Panel C. High income inequality neighborhoods			
Log of winning amount	0.0525**	0.0415	0.101**
	(0.0243)	(0.0323)	(0.0492)
Number of observations	2,484	1,222	1,222
Panel D. Low income neighborhoods			
Log of winning amount	0.0763***	0.0449	0.115**
	(0.0292)	(0.0367)	(0.0578)
Number of observations	2,465	1,201	1,201
Panel E. Apartment buildings			
Log of winning amount	0.119**	0.0654	0.225*
	(0.0483)	(0.0744)	(0.121)
Number of observations	1,046	453	453

Notes: This table reports the marginal effect of the log of the lottery prize on the count of bankruptcy in the winner's closest neighborhood (postal code) excluding winner's own bankruptcy in three event windows. This effect is estimated using a Negative Binomial model. All specifications include lottery product and winning year fixed effects. Control variables consist of DA level Gini coefficient, median income, population density, region's influence on urban core, DA numerical literacy, unemployment rate, family breakdowns, homeownership, age and gender distributions, and education levels. We consider postal codes with one prize during our study period, with randomly sized prizes of above $1,000 and below $150,000. Standard errors are in parentheses. *, **, *** denote significance at 10, 5, and 1 % level.

Table 3. No Effect of Lottery Prize Size on Winners' Neighbors prior to Winning

Event Window (years)	-1 to -2	-3 to -5	-1 to -5
Panel A. Whole sample			
Log of winning amount	-0.00283	-0.0113	-0.0127
	(0.0126)	(0.0159)	(0.0224)
Number of observations	6,829	6,829	6,829
Panel B. Urban, high density neighborhoods			
Log of winning amount	-0.00593	-0.0209	-0.0229
	(0.0142)	(0.0178)	(0.0250)
Number of observations	5,156	5,156	5,156
Panel C. High income inequality neighborhoods			
Log of winning amount	-0.00477	-0.0213	-0.0279
	(0.0164)	(0.0212)	(0.0292)
Number of observations	3,429	3,429	3,429
Panel D. Low income neighborhoods			
Log of winning amount	0.000470	0.00192	0.00658
	(0.0193)	(0.0262)	(0.0365)
Number of observations	3,386	3,386	3,386
Panel E. Apartment buildings			
Log of winning amount	-0.0298	-0.0458	-0.0711
	(0.0331)	(0.0405)	(0.0581)
Number of observations	1,562	1,562	1,562

Notes: This table reports the marginal effect of the log of the lottery prize on the count of bankruptcy in the winner's closest neighborhood (postal code) excluding winner's own bankruptcy in three event windows. This effect is estimated using a Negative Binomial model. All specifications include lottery product and winning year fixed effects. Control variables consist of DA level Gini coefficient, median income, population density, region's influence on urban core, DA numerical literacy, unemployment rate, family breakdowns, homeownership, age and gender distributions, and education levels. We consider postal codes with one prize during our study period, with randomly sized prizes of above $1,000 and below $150,000. Standard errors are in parentheses. *, **, *** denote significance at 10, 5, and 1 % level.

Table 4. No Effect of Lottery Size in outer Winners' Neighborhood (DA minus postal code)

Event Window (years)	0 to 2	3 to 5	0 to 5
Panel A. Whole sample			
Log of winning amount	-0.0123	-0.00623	-0.0231
	(0.0115)	(0.0156)	(0.0339)
Number of observations	4,924	2,370	2,370
Panel B. Urban, high density neighborhoods			
Log of winning amount	0.000591	0.00107	-0.00429
	(0.00679)	(0.00966)	(0.0168)
Number of observations	3,738	1,772	1,772
Panel C. High income inequality neighborhoods			
Log of winning amount	-0.0182	-0.00870	-0.0336
	(0.0194)	(0.0259)	(0.0577)
Number of observations	2,481	1,221	1,221
Panel D. Low income neighborhoods			
Log of winning amount	-0.0107	-0.0192	-0.0498
	(0.0200)	(0.0271)	(0.0614)
Number of observations	2,463	1,199	1,199
Panel E. Apartment buildings			
Log of winning amount	-0.0155	-0.00713	-0.0623
	(0.0479)	(0.0705)	(0.165)
Number of observations	1,046	453	453

Notes: This table reports the effect of the log of the lottery prize on the bankruptcy in the winner's outer neighborhood (Dissemination Area) excluding winner's postal. This effect is estimated using OLS. All specifications include lottery product and winning year fixed effects. Control variables consist of DA level Gini coefficient, median income, population density, region's influence on urban core, DA numerical literacy, unemployment rate, family breakdowns, homeownership, age and gender distributions, and education levels. We consider postal codes with one prize during our study period and prizes of above $1,000 and below $150,000. Standard errors are in parentheses. *, **, *** denote significance at 10, 5, and 1 % level.

Table 5. The Effect of Lottery Winning on Winners' Close vs. Distant Neighbors

Event Window (years)	0 to 2	3 to 5	0 to 5
Panel A. Whole sample			
Log of winning amount	0.0597***	0.0284	0.106*
	(0.0226)	(0.0306)	(0.0542)
Number of observations	9,856	4,742	4,742
Panel B. Urban, high density neighborhoods			
Log of winning amount	0.0469**	0.0163	0.0715
	(0.0222)	(0.0298)	(0.0468)
Number of observations	7,476	3,544	3,544
Panel C. High income inequality neighborhoods			
Log of winning amount	0.0669**	0.0688	0.160**
	(0.0313)	(0.0430)	(0.0791)
Number of observations	4,965	2,443	2,443
Panel D. Low income neighborhoods			
Log of winning amount	0.0915**	0.0705	0.195**
	(0.0357)	(0.0486)	(0.0887)
Number of observations	4,928	2,400	2,400
Panel E. Apartment buildings			
Log of winning amount	0.140**	0.151	0.438**
	(0.0687)	(0.105)	(0.204)
Number of observations	2,092	906	906

Notes: This table reports the effect of the log of the lottery prize interacted with the indicator for being in the winner's postal code on the count of bankruptcy. This effect is estimated using OLS. All specifications include lottery product and winning year fixed effects. Control variables consist of DA level Gini coefficient, median income, population density, region's influence on urban core, DA numerical literacy, unemployment rate, family breakdowns, homeownership, age and gender distributions, and education levels. We consider postal codes with one prize during our study period, with randomly sized prizes of above $1,000 and below $150,000. Standard errors are in parentheses. *, **, *** denote significance at 10, 5, and 1 % level.

Table 6. No Effect of Lottery Prize Size on Winners' Close vs. Distant Neighbors prior to Winning

Event Window (years)	-1 to -2	-3 to -5	-1 to -5
Panel A. Whole sample			
Log of winning amount	0.0115	0.00807	0.0196
	(0.0147)	(0.0187)	(0.0284)
Number of observations	13,644	13,644	13,644
Panel B. Urban, high density neighborhoods			
Log of winning amount	-0.00336	-0.0167	-0.0201
	(0.0144)	(0.0182)	(0.0265)
Number of observations	10,312	10,312	10,312
Panel C. High income inequality neighborhoods			
Log of winning amount	0.0209	0.0214	0.0423
	(0.0217)	(0.0262)	(0.0414)
Number of observations	6,850	6,850	6,850
Panel D. Low income neighborhoods			
Log of winning amount	0.0121	0.0196	0.0318
	(0.0230)	(0.0315)	(0.0472)
Number of observations	6,767	6,767	6,767
Panel E. Apartment buildings			
Log of winning amount	0.00642	0.00738	0.0138
	(0.0439)	(0.0553)	(0.0888)
Number of observations	3,124	3,124	3,124

Notes: This table reports the effect of the log of the lottery prize interacted with the indicator for being in the winner's postal code on the count of bankruptcy. This effect is estimated using OLS. All specifications include lottery product and winning year fixed effects. Control variables consist of DA level Gini coefficient, median income, population density, region's influence on urban core, DA numerical literacy, unemployment rate, family breakdowns, homeownership, age and gender distributions, and education levels. We consider postal codes with one prize during our study period, with randomly sized prizes of above $1,000 and below $150,000. Standard errors are in parentheses. *, **, *** denote significance at 10, 5, and 1 % level.

Table 7. Summary Statistics of Balance Sheet Data (Intensive Margins)

Variable	**Obs.**	**Mean**	**Std. Dev.**
Winning amount ($)	8841	6806.3	18654.2
Log of winning amount	8841	7.908	0.954
Winning year	8841	2009.7	2.5
Dummy Indicator of Assets Owned in Bankruptcy Balance Sheet			
Expensive Cars	8841	0.221	0.415
Expensive Houses	8841	0.079	0.269
Motorcycle	8841	0.018	0.135
Recreational equipment	8841	0.055	0.228
Cash	8841	0.037	0.188
Personal Effects	8841	0.283	0.450
Furniture	8841	0.012	0.108
Pension	8841	0.345	0.475
Securities	8841	0.037	0.189
DA Gini coefficient	8841	0.419	0.046
Population density (person per sq. km)	8841	3010.8	3564.6
Region type (1 to 8 score)	8841	1.712	1.410
Filer's age (years)	8841	43.0	13.1
Household size (count)	8841	2.144	1.373
Divorced indicator	8841	0.143	0.350
Prior defaults indicator	8841	0.200	0.400
Filed after the 2009 reform indicator	8841	0.569	0.495
Self-employed indicator	8841	0.080	0.271
Overuse of credit (0 or 1)	8841	0.549	0.498
Marital Breakdown (0 or 1)	8841	0.194	0.395
Unemployment (0 or 1)	8841	0.265	0.441
Insufficient Income (0 or 1)	8841	0.331	0.471
Business Failure (0 or 1)	8841	0.143	0.350
Health Concerns (0 or 1)	8841	0.225	0.418
Accidents / Emergencies (0 or 1)	8841	0.027	0.163
Student Loans (0 or 1)	8841	0.006	0.074
Gambling (0 or 1)	8841	0.031	0.174
Tax Liabilities (0 or 1)	8841	0.067	0.250
Loans cosigning (0 or 1)	8841	0.015	0.121
Bad / Poor Investments (0 or 1)	8841	0.033	0.178
Garnishee (0 or 1)	8841	0.012	0.110
Legal Action (0 or 1)	8841	0.022	0.146
Moving / Relocation (0 or 1)	8841	0.044	0.204
Substance Abuse (0 or 1)	8841	0.023	0.149
Supporting Relatives (0 or 1)	8841	0.079	0.269

Table 8. Magnitude of Lottery Prize effect on Balance Sheet of Bankruptcy Filers within Winners Postal Code After Winning

Event Window (years)	0 to 2	3 to 5	0 to 5
Expensive Cars	0.0207**	0.00201	0.0128*
	(0.00900)	(0.0129)	(0.00729)
Number of observations	2,656	1,230	3,923
Expensive Houses	0.0128**	0.00284	0.00877*
	(0.00620)	(0.00786)	(0.00457)
Number of observations	2,481	1,183	3,900
Motorcycle	0.00671**	9.04e-05	0.00366
	(0.00325)	(0.00616)	(0.00246)
Number of observations	2,389	961	3,769
Recreational equipment	0.00430	-0.00974	0.00118
	(0.00468)	(0.00908)	(0.00401)
Number of observations	2,586	1,170	3,900
Cash	0.00158	0.00211	0.00177
	(0.00427)	(0.00552)	(0.00301)
Number of observations	2,526	1,104	3,923
Personal Effects	-0.0201*	-0.00915	-0.0160*
	(0.0108)	(0.0136)	(0.00845)
Number of observations	2,660	1,267	3,927
Furniture	-0.000826	9.71e-05	-0.000512
	(0.00418)	(0.00854)	(0.00280)
Number of observations	1,834	607	3,206
Pension	-0.00802	-0.00484	-0.00516
	(0.0108)	(0.0140)	(0.00850)
Number of observations	2,658	1,267	3,927
Securities	0.00421	0.00745	0.00458
	(0.00384)	(0.00659)	(0.00311)
Number of observations	2,528	977	3,746

Notes: Definitions of Expensive House and Expensive Cars in text. All tests are Logit tests because all dependent variables are categorical as to whether an asset is present in the bankruptcy balance sheet or not. Standard errors are in parentheses. *, **, *** denote significance at 10, 5, and 1 % level.

Table 9. No Lottery Prize effect on Balance Sheet of Bankruptcy Filers within Winners Postal Code Prior to Winning

Event Window (years)	-1 to -2	-3 to -5	-1 to -5
Expensive Cars	0.00250	-0.0163	-0.00258
	(0.00966)	(0.0134)	(0.00780)
Number of observations	2,788	1,486	4,274
Expensive Houses	0.00483	-0.0111	0.00182
	(0.00677)	(0.0126)	(0.00489)
Number of observations	2,362	841	3,796
Motorcycle	-0.00165	-0.00514	-0.00162
	(0.00361)	(0.00844)	(0.00313)
Number of observations	2,440	1,017	3,770
Recreational equipment	0.00673	-0.00574	0.00268
	(0.00522)	(0.00784)	(0.00423)
Number of observations	2,686	1,431	4,151
Cash	0.00359	0.00907	0.00494
	(0.00470)	(0.00814)	(0.00390)
Number of observations	2,737	1,293	4,252
Personal Effects	-0.00463	0.0224*	0.00536
	(0.0106)	(0.0134)	(0.00836)
Number of observations	2,788	1,486	4,274
Furniture	-0.00165	0.0147	0.00141
	(0.00489)	(0.00938)	(0.00273)
Number of observations	2,059	527	3,458
Pension	-0.000117	0.00888	0.00361
	(0.0107)	(0.0152)	(0.00871)
Number of observations	2,788	1,486	4,274
Securities	-0.00249	-0.0109	-0.00700*
	(0.00442)	(0.00845)	(0.00398)
Number of observations	2,737	1,406	4,194

Notes: Definitions of Expensive House and Expensive Cars in the text. All tests are Logit tests because all dependent variables are categorical as to whether an asset is present in the bankruptcy balance sheet or not. Standard errors are in parentheses. *, **, *** denote significance at 10, 5, and 1 % level.