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Estimating Environmentally Adjusted Risks of Mortgage Arrears for Different Socioeconomic Groups of Borrowers

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Abstract:

Purpose: *The proper consideration of risk factors that can lead to the failure of a borrower to repay a mortgage is critical for both mortgage borrowers and lending institutions. Models for assessing the risk of mortgage arrears (MA) typically incorporate loan attributes and essential characteristics of the borrower, including net income, family size, age, education, and credit history. However, such standard MA models exclude environmental risk factors, which increase, as we hypothesize, the MA risk.*
Design/Methodology/Approach: *We analyzed 90,000 individual mortgage records obtained from a leading commercial bank in Israel to verify this hypothesis. In the analysis, the mortgage records were geo-referenced by their seven-digit ZIP codes and linked to air pollution data and several other locational attributes. The analysis was performed using a Cox-type proportional hazard model.*
Findings: *The study shows that residential exposure to high levels of air pollution tends to increase the MA risk by about 10%–25%, depending on the type of air pollutant and exposure level. We attribute this finding to the fact that exposure to air pollution may reduce productivity and increase work absenteeism, thus making mortgage repayment more difficult.*
Practical implications: *The importance of the study is due to its three main novelty aspects: First, it suggests an empirical approach to adjusting MA risk estimates by accounting for environmental attributes of residential properties. Second, the analysis shows that borrowers' and mortgage's attributes (such as net monthly income, family size, and LTV ratio) tend to increase the MA risk asymmetrically for different groups of borrowers.*
Originality: *The study demonstrates the utility of adding air pollution variables to the list of MA risk predictors, which helps to introduce important information not captured by other observables. To the best of our knowledge, this is the first study that assesses environmentally adjusted MA risks for different socioeconomic groups of borrowers.*

Keywords: *Mortgage arrears, risk assessment, modelling.*

JEL codes: *G3, M2*

Type: *Research paper.*

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1. Introduction

Since 2010, tresidential loan market in OECD countries has expanded by 5% every year, and it currently constitutes about 70% of the total credit growth (OECD, 2017). In the USA alone, between 2010 and 2018, the mortgage sector has increased from \$14.3 trillion to \$15.4 trillion, signifying a nominal increase of about 7.6% (Federal Reserve Bank [FED], 2018). During the same period, the debt of private households to banks and lending institutions increased from \$2.6 trillion to \$4.0 trillion, that is by about 53% (FED, 2019). The credit market in the UK shows a similar trend, with household debt increasing from \$1.7 trillion in 2012 to \$2.0 trillion in 2017, thus raising doubt as to the financial stability of the borrowers, since any increase in the interest rate or decrease in real income can make high-leveraged borrowers extremely vulnerable (Bank of England [BOE], 2018).

For the borrower, the consequences of failure to repay a mortgage can be far-reaching. If the mortgage contract is impaired, the borrower is forced to pay the remaining debt with a premium. Then, if the delinquent debt is not paid and a repayment schedule is not fixed, the lender can begin the foreclosure process (Ferreira and Gyourko, 2015). This process affects the borrower on several levels: economically, by lowering the credit score; socially, by necessitating a move to another location, away from friends and family; and, physiologically, by causing stress in family relationships and other areas of life, and negatively affecting the borrower’s wellbeing and health (Downing, 2016).

High rates of mortgage arrears (MAs) may equally be damaging to the lender. In accordance with accounting regulations, banks are required to write off bad debts. Increasing numbers of MAs may reduce profit and, in extreme cases, lead to the financial collapse of the lender (Waldron & Redmond, 2016). High MA rates can also be damaging to the national economy as a whole and may require state intervention. This was the case during the 2008 subprime crisis, when the federal government was forced to support commercial banks and take over the Fannie Mae and Freddie Mac mortgage agencies through a federal act (Frame, Fuster, Tracy, and Vickery, 2015). The direct damage to the U.S. economy alone from the crisis is estimated at \$14 trillion (Erkens, Hung, and Matos, 2012), and the global gross domestic product (GDP) was reduced by 8.35% (Ball, 2014).

To predict the risk of MA by borrowers and minimize the default risk, comprehensive and accurate risk-assessment models are needed. The existing models are based on the individual attributes of the borrowers, including age, education, family size, job position, and net income. In addition, the models include the basic attributes of the loan, such as loan-to-value (LTV) ratio, loan-to-income (LTI) ratio, size of monthly repayments, etc., (Gete and Reher, 2016).

A common definition of mortgage is “a long-term loan offered to buy an apartment or house” (Collins English Dictionary, 2017). Since buildings stand in fixed locations, they may be subject to damage due to local environmental conditions, such as flooding and earthquakes, and security risks near the borders. Other environmental factors, such as exposure to air pollution, may also affect the borrower's ability to make regular mortgage payments, because such factors may reduce productivity and increase work absenteeism, thereby making mortgage repayment more difficult (Borochov *et al.*, 2019). While standard MA risk-assessment models usually do not incorporate any of these environmental risk factors, our hypothesis is that these *environmental factors may increase the MA risk asymmetrically for different groups of borrowers*.

In this paper, we attempt to verify the hypothesis by using more than 90,000 individual mortgage records from 2010–2011, obtained from a leading commercial bank in Israel. The mortgage records are geo-referenced by their seven-digit ZIP-codes and merged with air pollution data obtained from local air-quality monitoring stations. Several locational attributes of the properties, including proximity to the nearest main road, and proximity to conflict zones are also considered. The analysis was performed using Cox-type proportional hazards models. After identifying the variables that are significantly associated with the MA incidence, we estimated *environmentally adjusted MA risks for different socioeconomic groups of borrowers, stratified by income, family size, and the LTV ratio*.

Although several previous studies analyzed various environmental risk factors in the context of real estate, most of these studies focused on home values (Gerardi *et al.*, 2013; Wu and Dorfman, 2018; Sayag, 2012). To the best of our knowledge, only one study, by Borochov *et al.* (2019), attempted to assess the effect of environmental factors on the MA risk. Although the study estimated odds ratios for several air pollution variables, it did not attempt to calculate *environmentally adjusted risk estimates of MAs for different socioeconomic groups of borrowers*, which we calculate in this study.

2. Factors Affecting the MA Risk

2.1 Macroeconomic Factors

Empirical studies mention several factors that may cause MAs, including the financial state of the borrower and various attributes of the asset. According to the central banks in the OECD countries, the main factors, influencing the MA risk, are the LTV ratio and the proportional share of the monthly payback in the family's net income. Before the 2008 financial crisis, banks allowed to finance up to 100% of the asset value (Elul, Souleles, Chomsisengphet, Glennon, and Hunt, 2010; Ferreira, Gyourko, and Tracy, 2010). After the crisis, central banks in many OECD countries reduced the maximum LTV ratio to less than 70%. This reduction was a result of the so-called "negative asset" phenomena, characterized by house values that fell below the mortgage value (Fuster and Willen, 2017).

In 2008 and 2009, the foreclosure of many assets in the USA by mortgage agencies and banks created a mass supply glut in a short time. The increased supply and weakening demand resulted in a drop in home prices, bringing the value of some assets below the purchase price and even below the mortgage value. The negative asset values pushed the real-estate market even further down because many borrowers opted to commit a strategic default in order to get rid of depreciating assets (Bradley, Cutts, and Liu, 2015). This led to the restriction of borrower leverage and of monthly payback to less than 50% of borrowers' net income (Igan and Kang 2011).

2.2 The Mortgage-Lending Policy in Israel

The total volume of mortgages in Israel currently stands at NIS340 Billion (US$100 Billion), or about 29% of the national GDP. Of this amount, NIS2.5 billion worth of mortgages (0.7%) is estimated to be in deep arrears, and 30% of this amount is treated by active collection methods. In addition, the state invests another NIS1.0 billion in mortgage loans that are not paid on time (GOI, 2014).

Until 2008, borrowers in Israel were required to choose mortgages linked to one of two types of interest rate -- either variable (linked to the prime/subprime interest rate) or fixed, that is, linked to the consumer-price index (Machnes, 2018). Many mortgages that defaulted in the wake of the 2008 global financial crisis were linked to the prime interest rate. The matter is that the size of the monthly paybacks followed the rate’s fluctuations and often increased dramatically within a short period after the mortgage issuance. To reduce the mortgage default risk, the BOI obligated lenders to adjust their interest policies by offering mortgages at a mixed interest rate (Machnes, 2018).

2.3 MA Risk-Assessment Models

MA risk-assessment models, used in previous studies, are mainly based on personal attributes of the borrowers and basic characteristics of the neighborhood (Peter and Peter, 2011; Gross and Población, 2017; Byrne, Kelly, and O’Toole, 2017; Kelly and O’Toole, 2018). Thus, Peter and Peter (2011) investigated the relationship between mortgage-default risk and socioeconomic and housing characteristics of homeowners in Western Australia. The data used in the study contained detailed information about the demographic structure, tenure, housing costs, and income of the households, as well as the affordability and adequacy of the buildings. A binary logistic regression model was used to identify variables that significantly affect the MA risk. The model took several socioeconomic factors into consideration, including LTV, net income, age, education, and the socioeconomic status (SES) of the neighborhood. The study revealed that the borrower income and the LTV ratio were significant MA determinants, while location was not, leading the researchers to conclude that more detailed information may be needed to identify the effect of locational attributes on the MA risk more precisely.

Several other studies (Oreski *et al.*, 2012; Feinstein, Sullivan, and Jack, 2012; Gan, Li, Wang, and Kao, 2012; Chi and Hsu, 2012) linked the MA risk to the national credit score system. Thus, Chi and Hsu (2012) developed a genetic algorithm that combines the national scoring system and the borrower's credit behavior and applied this algorithm to the analysis of the MA risk. The results showed that the hybrid approach, which incorporates microeconomic variables that represent individual attributes of the borrowers, is more accurate than a model solely based on the borrower's personal finances and socioeconomic attributes.

In a separate study, Fitzpatrick and Mues (2016) developed an MA risk-assessment model that incorporates various income-related ratios (repayment-to-income, LTI, etc.) and the current interest rate. In addition to these standard economic variables, the geographic location of the property and the loan origination during the years 2004–2009 were included as MA predictors. The researchers emphasized that the use of boosted regression, which combines many variables that are individually insignificant but together informative, outperforms ordinary logistic regression. The significant variables in the model are repayment-to-income, LTI, current LTV, loan age, and interest rate. Although the contribution of the property's location was found to be marginally significant, it carried only a minimum weight of about 4%, in compare to the 18% contribution of the repayment-to-income ratio and the 14% contribution of the LTI ratio.

In another recent study, Pereira, Ferreira, and Chang (2017) defined 107 criteria for evaluating the MA risk, including the client profile, contract elements, motivation of the bank front-desk employees, and property-related factors, such as property type and incorporated infrastructures. In a separate study, Chambers *et al.* (2019) investigated the relationship between mortgage foreclosures, homeownership, and cardiovascular disease risk by including the health status of the homeowner as a potential predictor of mortgage failure. The study revealed a significant correlation between MA incidence and local prevalence of heart diseases, leading the researchers to conclude that living in a distressed area may negatively affect the wellbeing of mortgage borrowers even before the actual increase in foreclosure rates.

In a separate study carried out in Israel, Borochov *et al.* (2019) assessed the effect of various environmental factors on the MA risk. Although the study estimated the odds ratios for several air pollution variables, it did not attempt to calculate environmentally adjusted risk estimates of MAs for different socioeconomic groups of borrowers. The study was also based on a relatively simple binary logistic model for quantifying the factors affecting the MA risk. However, this model may be insufficient since it does not take the duration of the period between the mortgage issuance and the mortgage failure into consideration.

3. Study Methodology

3.1 Mortgage Data

The mortgage data for the present analysis were retrieved from a countrywide database maintained by the country's leading commercial bank, *Mizrahi-Tfahot* Ltd., which generates about 30% of all mortgages in Israel (BOI, 2013). The individual mortgage records available for analysis cover the two-year period between 2010 and 2011. Out of 91,537 records retrieved from the database, there are 46,633 records for 2010 and 44,904 records for 2011 (Table 1 and Figure 1). The records contain information on the geographic location of individual mortgaged assets (referenced by seven-digit ZIP-codes), loan characteristics (the total mortgage amount and the LTV ratio), and several socioeconomic attributes of the borrowers, including age of the main borrower, education, income, and total number of persons in the family.[3] The mortgage records were retrieved at the end of 2016. If, until then, the mortgage borrower was in arrear for *three months or more* since the mortgage issuance, the value of the MA variable was set to 1. Otherwise, it was set to 0. In addition, the duration of the time period between the mortgage issuance and an MA incidence, if occurred, was retrieved from the database, to enable a more advanced statistical analysis of the data.

3.2 Air Pollution Data

Several studies (Evans *et al.*, 2002; Greenberg *et al.*, 2015; Wargocki and Wyon, 2017) link exposure to high levels of air pollution to greater morbidity, which may potentially increase the MA risk. To verify this assumption, we obtained air pollution data from the national air-quality monitoring network, which consists of 140 monitoring stations located all over the country, from the town of Carmiel in the north to Eilat in the south (Figure 1). The information on five routinely monitored air pollutants — nitrogen oxides (NO_x), sulfur dioxide (SO_2), ozone (O_3), and particulate matter ($PM_{2.5}$ and PM_{10}), — was collected as annual averages, in parts per billion (ppb), for the year of interest (that is, either 2010 or 2011), and linked to the geographic location of individual properties by the "nearest-monitor" method (Kioumourtzoglou *et al.*, 2014).[4]

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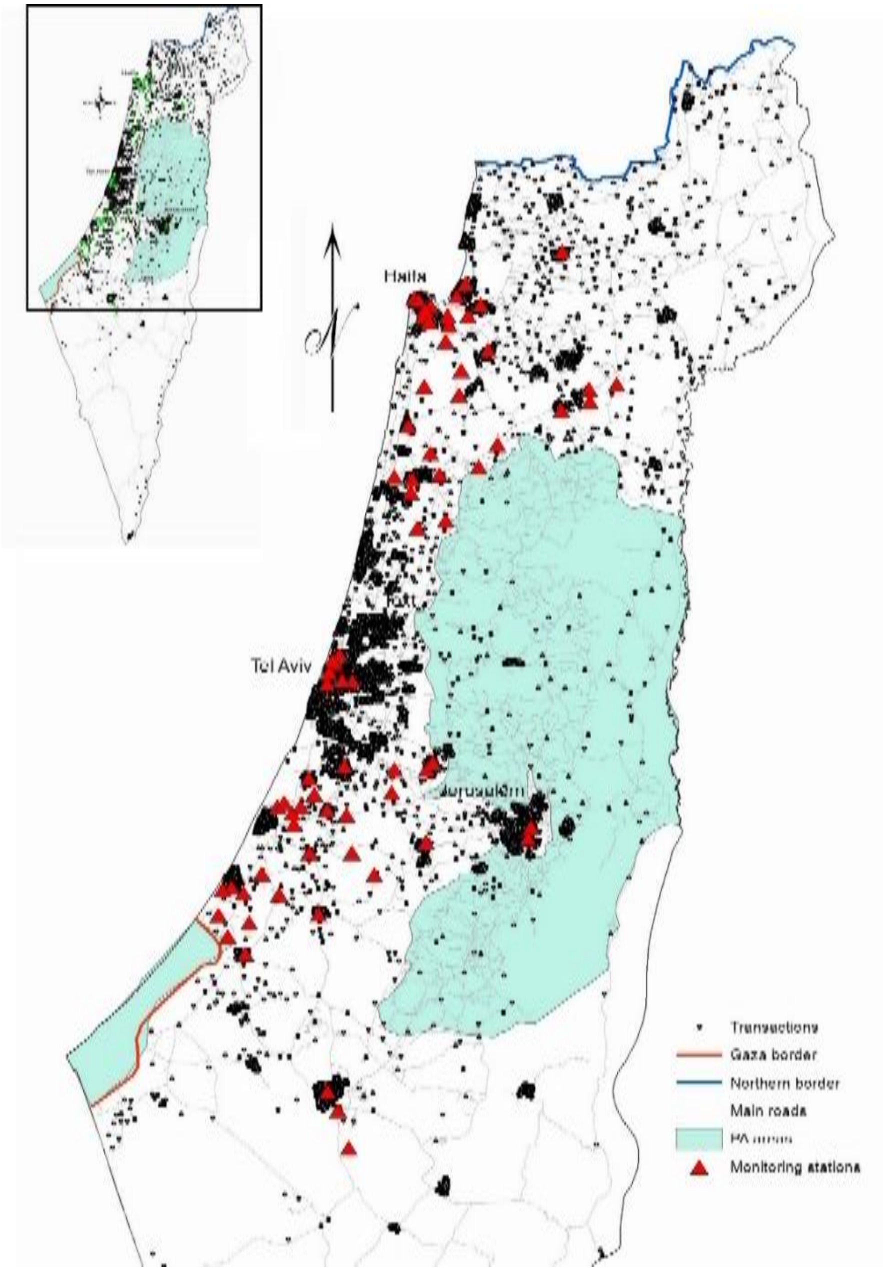
[3] *In the study, LTV was calculated for the date of mortgage issuance, not as current LTV, due to the fact that value assessment is performed by the bank only once at the time of mortgage issuance.*

[4] *Depending on the type of measurement equipment installed, the air-quality monitoring stations measure different combinations of air pollutants. In this case, there were 129 stations that recorded all five pollutants and 11 stations that recorded only NO_x, $PM_{2.5}$, and PM_{10}.*

Figure 1. *Map of the study area*



Notes: *The map shows the northern and central parts of the country, where the most mortgage transactions take place. In the top left corner, this area is marked within a map of the whole country.*
Source: *Own study.*

Table 1. *Descriptive Statistics of Research Variables (2010–2011, Pooled Dataset)*

Variable	Min	Max	Mean	Std. Dev.	%
MA event:					
• Yes	-	-	-	-	11.3
• No	-	-	-	-	89.7
Age of the main borrower (years)	18.00	70.00	47.52	10.95	-
Education:					
• Academic	-	-	-	-	56.50
• Associate	-	-	-	-	32.20
• High school	-	-	-	-	9.10
• Elementary	-	-	-	-	2.20
Net monthly income, NIS (ln)	7.60	14.22	9.56	0.53	
Mortgage amount, NIS (ln)	9.23	16.08	12.40	1.07	-
Loan-to-value (LTV) ratio (%)	0.10	1.00	0.55	0.19	-
Family size, persons	1.00	16.00	3.83	2.01	-
Air pollution estimates (annual averages in ppb):					
• NOx	3.00	94.00	34.84	18.98	-
• O_3	42.0	103.0	66.96	11.09	-
• PM_{10}	36.00	74.00	56.37	9.33	-
• $PM_{2.5}$	14.00	29.00	23.00	2.55	-
• SO_2	1.00	10.48	3.74	1.46	-
D_road, m	0.00	4324.34	110.12	131.21	-
Property location in Palestinian Authority (PA) areas:					
• Yes	-	-	-	-	8.00
• No	-	-	-	-	92.00
D_north, km (ln)	3.35	12.88	11.48	0.76	
D_gaza, km (ln)	7.20	12.31	11.11	0.57	
Valid N (listwise)	88,654				

Source: *Own study.*

3.3 Locational Characteristics of the Properties

For each residential property in the database, we calculated the proximity to the nearest main road (D_road). This was used as a proxy for routinely unmeasured air pollutants, such as volatile and semi-volatile organic confounds, that are often associated with motor traffic (Cassee *et al.*, 2013). Two additional location variables included in the analysis as potential predictors of MA incidence were: the aerial proximities to the northern border with Lebanon and to the border with the Gaza strip in the south (Figure 1). These borders are a source of ongoing armed conflicts and security risks (Greene, Itzhaky, Bronstein, and Solomon, 2018; Elster, Zussman, and Zussman, 2017), causing economic instability that may increase MA rates.

Currently, about 85,000 Israeli homes are located outside the 1949 armistice line (aka the Green Line), in the territories controlled by Israel and known as Judea and Samaria, or, alternatively, as the Jordan river's West Bank (Central Bureau of Statistics [CBS], 2018a). These areas are disputed by Israel and the Palestinian

Authority (PA), and international sanctions are imposed on industries and products manufactured there (Botta, 2010). An additional dichotomous variable, identifying PA-located residential properties, was included in the analysis as an MA predictor, since location in such areas may affect the loan repayment ability of the borrowers due to unstable jobs and wages, and loss of working hours during road closures, security disturbances, etc. The proximity calculations were performed using the "spatial join" tool of the ArcGIS^{TM}10.x software, applied to layers (maps) obtained from the National Survey of Israel (SOI) (SOI, 2018).

Another environmental variable included in the analysis was the SES of the neighborhood in which the property is located. For data collection purposes, the Israel Central Bureau of Statistics divides the country into small census areas, which we used as supporting units in the analysis. These small statistical areas are similar in size to census blocks in the USA, containing on the average about 5,000 persons, and considered to be homogeneous in terms of socio-demography attributes of their residents. The neighborhood SES information was obtained from CBS (2018b), which classifies localities and residential neighborhoods into 10 SES clusters, ranging from low (1) to high (10).

3.4 Statistical Analysis

The Cox proportional hazards regression (Harrell, 2015) was used to identify and measure the effect of various factors on MA incidence. As compared to more commonly used binary logistic models for predicting MA events, such as those used by Borochov *et al.* (2019) and Carter and Signorino (2010), the Cox proportional hazards model accounts not only for the event incidence (yes/no), but also for the duration of time until the event occurrence, thereby helping improve the statistical power of the model and reveal significant covariates (Barros and Hirakata, 2003).

The hazards function, denoted by $h(t)$, is determined by a set of p covariates ($x_1,x_2,\ldots,x_p$), and can be interpreted as the risk of the event incidence (such as MA) at time t. In its general form:

$$h(t) = h_0(t) \times exp(b_1x_1 + b_2x_2 + \ldots + b_px_p), \quad (1)$$

where t represents the survival time (i.e., the time to the event), b_1, b_2, … b_p are regression coefficients that measure the effect size of the covariates, and h_0 is the so-called "baseline hazard", which corresponds to the value of the hazard function if all the covariates (x_1, x_2, …., x_p) equal zero. The fact that $h(t)$ is a function of t indicates that the hazard effect may vary over time.

In our study, we examined two types of Cox proportional hazards models and compared their performance. The first model contains only loan attributes and socioeconomic characteristics of the borrower (Model 1):

$$MA(t) = MA_0(t) \times exp(b_1\boldsymbol{IND}_i + b_2\boldsymbol{PROP}_i + b_3SES_i + b_4Year2011) \quad (2)$$

where $MA(t)$ represents the risk of an MA event at time t; $\boldsymbol{IND}_i$ is a vector of individual attributes of the borrower, including age, education (academic, associate, high school, or elementary), net monthly income of the family in NIS (ln), and family size (persons); $\boldsymbol{PROP}_i$ is a vector of the mortgage-related attributes, including the total mortgage amount in NIS (ln) and the LTV ratio (%); *Year2011* is a binary variable representing the mortgage issuance in the year 2011 (yes/no); and SES_i is the socioeconomic status of the neighborhood.

The second model (Model 2) contains the same socioeconomic and individual attributes, but also adds air pollution and property-specific locational characteristics:

$$MA(t) = MA_0(t) \times exp\,(b_1\boldsymbol{IND}_i + b_2\boldsymbol{PROP}_i + b_3SES_i + b_4Year2011 + \boldsymbol{POL_i} + PA + Roads_i + \boldsymbol{BORD_i}), \quad (3)$$

where $\boldsymbol{POL_i}$ is a vector of air pollution estimates for the air pollutants NO_x, O_3, PM_{10}, $PM_{2.5}$, and SO_2 (in ppb); *PA* is a dummy variable that represents the location relative to the Green Line (inside/outside); $Roads_i$ is the aerial distance from property i to the nearest main road (m); and $\boldsymbol{BORD_i}$ is a vector of the aerial distances from the Northern or Gaza strip borders in km (D_north (ln) and D_gaza (ln), respectively).

If findings verify that MA incidence is affected by the environmental attributes of the properties, then the environmental variables under study should emerge as statistically significant predictors of the MA risk in Model 2 (**H_1**). Alternatively, if the **H_0** hypothesis is confirmed, the environmental variables would have no significant influence on the MA risk. The analysis was performed with the IBM SPSS[TM]v25 software, using its survival regression module.

4. Results

4.1 General Trends

Table 1 shows selected descriptive statistics of the research variables from the pooled dataset, while Table 2 shows the descriptive statistics for each year separately. As Table 1 shows, out of the total number of 88,654 transactions recorded in 2010–2011, 10,017 transactions (11.3%) were in arrears, with regular payments delayed by three months or more.[5] The number of MAs was 1% higher in 2010 than in 2011: 11.8% vs. 10.8%, respectively (Table 2). The drop in the MA rates in 2011 can, apparently, be attributed to the reduced interest rate and economic recovery in the aftermath of

[5] *The difference between an MA and a deep mortgage default treated by active collection methods). The present study uses MA (i.e., payment delayed by three months or more), while the official statistics published by the BOI (BOI, 2019) refer to deep arrears or mortgage defaults.*

the 2008–2009 global economic crisis that lead to a reduction in the countrywide unemployment rates (CBS, 2018a).

In Table 2, the average LTV ratio is 55% in 2010 and 53% in 2011, both well below the 75% threshold instituted by the BOI (Tzur-Ilan, 2017). Such relatively low LTV ratios reflect a reasonable reaction of the lender to the recent economic crises—the 2008 subprime crisis in the USA and the 2010 European debt crisis—a reaction that aims at reducing loan-associated risks.

Although the mean levels of air pollution exposure reported in Tables 1–2 are mostly below the local air pollution standards,[6] a relatively large variation in the pollution levels estimated for individual properties is observed: 3.0–94.0 ppb for NO_x, 42.0–103.0 ppb for O_3, 36.0–74.0 ppb for PM_{10}, 14.0–29.0 ppb for $PM_{2.5}$, and 1.1–10.48 ppb for SO_2. This indicates that at least some properties in the sample are located in places with extremely high levels of air pollution.

4.2 Factors Affecting MA Incidence

Tables 3 and 4 report the results of the Cox proportional hazards modeling of the factors that affect MA incidence. Table 3 reports the results of using Model 1 and Model 2. As previously mentioned, Model 1 only includes the socioeconomic characteristics of the borrowers and the loan attributes, whereas Model 2 adds air pollution characteristics and proximity variables. Table 4 only displays the statistically significant variables, filtered out by the stepwise regression procedure (Models 1A–2A).

Table 2. *Descriptive Statistics of Research Variables (2010–2011, Separated Datasets)*

Variable	Min	Max	Mean	StdDe.	Count (%)	Min	Max	Mean	Std Dv.	Count (%)
	2010					**2011**				
MA event:										
• Yes (%)	-	-	-	-	6304 (11.8%)	-	-	-	-	4868 (10.8%)
• No (%)	-	-	-	-	47044 (88.2%)	-	-	-	-	40036 (89.2%)
Age of the main borrower (years)	18	70	47.52	11.09	-	18	70	46.81	10.91	-
Education:										
• Academic	-	-	-	-	56.50%	-	-	-	-	59.80%
• Associate	-	-	-	-	32.20%	-	-	-	-	31.50%
• High school	-	-	-	-	9.10%	-	-	-	-	6.90%
• Elementary	-	-	-	-	2.20%	-	-	-	-	1.80%

[6] *The maximum permitted daily levels of air pollution in Israel currently stand at 35 ppb for NO_x, 67 ppb for O_3, 56 ppb for PM_{10}, 23 ppb for $PM_{2.5}$, and 3.8 ppb for SO_2 (IMEP, 2011), like the concentrations permitted in North America and Western Europe (Josipovic, Annegarn, Kneen, Pienaar, and Piketh, 2010).*

Variable	Min	Max	Mean	StdDe.	Count (%)	Min	Max	Mean	Std Dv.	Count (%)
	2010					**2011**				
Net monthly income, NIS (ln)	0	14.22	9.53	0.57		0	15.42	9.60	0.54	-
Mortgage amount, NIS (ln)	3.91	16.45	12.40	1.07	-	5.23	16.77	12.39	1.11	-
Loan-to-value ratio (%)	0.1	1.00	0.55	0.19	-	0.1	1.23	0.53	0.18	-
Family size, persons	1.00	16.00	3.81	2.02	-	1.00	17.00	3.85	2.11	-
Air pollution estimates (annual averages in ppb):										
• NOx	5.64	94.00	38.27	21.27	-	3.00	80.00	31.17	15.40	-
• O_3	50.76	103.40	66.15	12.27	-	41.55	96.00	67.84	9.62	-
• PM_{10}	44.00	74.00	61.80	8.14	-	36.00	63.00	50.62	6.68	-
• $PM_{2.5}$	19.00	29.00	23.52	2.52	-	14.00	26.00	22.17	2.39	-
• SO_2	1.13	8.27	3.49	1.36	-	1.00	10.48	4.02	1.53	-
D_road, m	0.00	4324.49	110.17	131.81	-	0.00	4324.49	110.00	134.08	-
Palestinian Authority (PA) areas:	-	-	-	-		-	-	-	-	
• Yes	-	-	-	-	8%	-	-	-	-	8.3%
• No	-	-	-	-	92%	-	-	-	-	91.7%
D_north, km (ln)	3.35	12.88	11.48	0.76		3.35	12.88	11.48	0.76	
D_gaza, km (ln)	7.20	12.31	11.11	0.57		7.20	12.31	11.10	0.58	
Valid N (listise)	46,633					44,904				

Table 3. *Factors Affecting Mortgage Defaults, for 2010–2011*

Variable	Model 1 B	Model 1 HR (Exp (B))	Model 1 HR 95% Confidence Interval (CI) Lower	Model 1 HR 95% CI Upper	Model 2 B	Model 2 HR (Exp (B))	Model 2 HR 95% CI Lower	Model 2 HR 95% CI Upper
Socioeconomic variables:								
Age (years)	0.002	1.002	1.000	1.004	0.002	1.002	1.000	1.004
Education:								
• Academic	-0.485**	0.616	0.548	0.692	-0.457**	0.633	0.563	0.712
• Associate	-0.146	0.864	0.769	0.972	-0.124	0.884	0.786	0.994
• High school	-0.072	0.931	0.819	1.057	-0.044	0.957	0.842	1.087
Net monthly income, NIS (ln)	0.009	1.009	0.969	1.050	-0.059	0.942	0.891	0.997
Mortgage amount NIS (ln)	-0.098**	0.906	0.890	0.924	-0.101**	0.904	0.887	1.052
Loan-to-value ratio (LTV, %)	0.005**	1.005	1.004	1.006	0.005**	1.005	1.004	1.006
Family size, persons	0.020**	1.020	1.010	1.030	0.013**	1.014	1.003	1.024
Neighborhood socioeconomic status (SES)	9.59E-05	1.000	0.996	1.004	$1.88E^{-04}$	1.000	0.996	1.004
Year 2011 dummy	-0.162	1.002	1.000	1.004	-0.059	0.942	0.891	0.997
Environmental variables:								
NOx ,ppb	-	-	-	-	0.003**	1.003	1.001	1.004
O_3,ppb	-	-	-	-	0.007**	1.007	1.004	1.009
PM_{10},ppb	-	-	-	-	0.007**	1.007	1.004	1.011
$PM_{2.5}$,ppb	-	-	-	-	0.026**	1.027	1.017	1.036
SO_2,ppb	-	-	-	-	0.042**	1.043	1.028	1.058
D_road, m	-	-	-	-	$8.57E^{-05}$	1.000	1.000	1.000

Variable	B	HR (Exp (B))	Lower	Upper	B	HR (Exp (B))	Lower	Upper
Palestinian Authority (PA) (yes/no)	-	-	-	-	0.058	1.059	0.598	1.140
D_north, km (ln)	-	-	-	-	6.08E-08	1.000	1.000	1.000
D_gaza, km (ln)	-	-	-	-	1.000	1.000	1.000	1.000
No. of cases	88,655				88,655			
X^a	664.334				887.730			
-2 Log likelihood	241769.536				241556.783			

Notes: Method: Cox proportional hazards model; independent variables: MA event (Yes = 1, No = 0) and duration of the MA event in months; all explanatory variables are included. HR = proportional hazards ratio; * indicates a 0.05 significance level; ** indicates a 0.01 significance level (two-tailed). X^a is the goodness-of-fit statistic.
Model 1: Socioeconomic variables included, environmental and locational variables excluded; **Model 2**: Environmental and locational variables added.

Table 4. *Factors Significantly Affecting Mortgage Defaults, for 2010–2011*

Variable	Model 1A B	HR (Exp (B))	HR 95% Confidence Interval (CI) Lower	Upper	Model 2A B	HR (Exp (B))	HR 95% Confidence Interval (CI) Lower	Upper
Socioeconomic variables:								
Net monthly income, NIS (ln)	-0.830**	0.920	0.886	0.956	-0.064**	0.933	0.898	0.969
Mortgage amount NIS (ln)	-0.115**	0.891	0.875	0.907	-0.119**	0.887	0.871	0.903
Loan-to-value ratio (LTV, %)	0.004**	1.004	1.003	1.005	0.004**	1.005	1.003	1.006
Family size, persons	0.023**	1.023	1.014	1.033	0.016*	1.005	1.003	1.006
Environmental variables:								
O_3,ppb	-	-	-	-	.005**	1.005	1.003	1.006
PM_{10},ppb	-	-	-	-	.008**	1.008	1.005	1.011
$PM_{2.5}$,ppb	-	-	-	-	.026**	1.027	1.018	1.035
SO_2,ppb	-	-	-	-	.052**	1.054	1.040	1.068
No. of cases	88,655				88,655			
X^a	254.864				524.151			
-2 Log likelihood	242903.470				241104.980			

Notes: Method: Cox proportional hazards model, forward regression; dependent variables—MA event (Yes = 1, No = 0) and duration to the MA event in months; only significant variables are included. HR = proportional hazards ratio; * indicates a 0.05 significance level; ** indicates a 0.01 significance level (two-tailed). X^{2a} is the goodness-of-fit statistic.
Model 3: Socioeconomic variables are included, environmental and locational variables are excluded;
Model 4: Environmental and locational variables added.

Model 1 (Table 3) flags the following variables as statically significant predictors of the MA incidence: academic education (proportional Hazards Ratio [HR] = 1.002, 95% confidence interval (CI) = 1.000, 1.004; $p<0.01$); mortgage amount (ln) (HR = 0.904, 95% CI = 0.887, 1.052; $p<0.01$); LTV ratio (HR = 1.005, 95% CI = 1.004, 1.006; $p<0.01$), and family size (HR = 1.014, 95% CI = 1.003, 1.024; $p<0.01$). These hazard ratios indicate that the risk of MA tends to increase, all else being equal, with an increase in the LTV ratio and family size of the borrower, and to decrease with education and mortgage amount ($p<0.01$).

Model 2 includes all these factors and also adds five air pollution variables — NOx, O_3, PM_{10}, and $PM_{2.5}$, SO_2 — as significant predictors of MA incidence ($p<0.01$). None of the other locational variables (such as proximity to the borders and location inside the Green Line) were found to be statistically significant in this model ($P>0.05$).

Table 3 confirms positive associations between air pollution variables and MA risk, NO_x (b = 0.003, $p<0.01$), O_3 (b = 0.007, $p<0.01$), PM_{10} (b = 0.07, $p<0.01$), $PM_{2.5}$ (b =

0.026, $p<0.01$), and SO_2 (b = 0.042, $P<0.01$), indicating that the MA risk tends to increase, all else being equal, with air pollution exposure. Four of these variables retain their statistical significance in Model 2A, which only includes statistically significant variables: O_3 (b = 0.05, $p<0.01$), PM_{10} (b = 0.008, $p<0.01$), $PM_{2.5}$ (b = 0.026, $p<0.01$), and SO_2 (b = 0.052, $p<0.01$) (Table 4, Model 2A).

According to the explanation proposed, exposure to air pollution boosts the MA risk by reducing productivity and increasing work absenteeism, which makes it more difficult for a borrower to make mortgage payments. However, it is also possible that air pollution levels at the place of the property's location capture unobserved neighborhood qualities or initial risk profiles of borrowers such as their willingness to live in polluted areas due to the availability of affordable housing there. To verify this possibility, we introduced into the models' data on air pollution one year following the mortgage origination, in order to determine whether the ongoing pollution still increases MA rates.

Table 5 reports the results of the reanalysis. As Table 5 shows, most air pollution variables (such as NOx, PM_{10}, $PM_{2.5}$ and SO_2) retain their statistical significance levels or even became more statistically significant upon 1-year forward shifting ($p<0.01$), thus confirming our initial hypothesis that exposure to air pollution indeed appears to reduce the borrower's ability to make mortgage repayments, and not just reflects the initial risk profiles of the borrowers or some local unobservable factors.

Characteristically, the model fit increases after the environmental variables are added to the set of predictors, as indicated by the Hosmer-Lemeshow (H-L) goodness-of-fit test. In particular, after adding these variables to the list of predictors, the values of H-L X^2 increase from 254.9 (Model 1A; Table 4) to 524.2 (Model 2A; Table 4), indicating that the inclusion of the air pollution variables does improve the model estimates.

5. MA Risk Assessment for Different Groups of Borrowers

To assess the MA risks for different groups of borrowers, we divided all the records in our database into several clusters, combining three variables — the LTV ratio (%), family size (persons), and net monthly income, NIS (ln), — all of which were found to be statistically significant predictors of MA incidence by Model 1. For each variable, three clusters were formed — *low*, *medium*, and *high*, — reflecting the differences in the observed values. The classification was performed using the hierarchical cluster analysis method, performed with the IBM SPSS™v25 software.

Table 5. *Factors Affecting Mortgage Defaults, for 2010–2011 (Air pollution levels are estimated for the year following the mortgage issuance (see text for explanations))*

Variable	Model 3			
	B	HR (Exp (B))	HR 95% CI Lower	HR 95% CI Upper
Socioeconomic variables:				
Age (years)	0.000	1.000	0.998	1.003
Education:				
• Academic	-0.309**	0.734	0.628	0.860
• Associate	-0.062	0.940	0.804	1.099
• High school	0.012	0.889	1.012	0.856
Net monthly income, NIS (ln)	-0.048	0.953	0.902	1.007
Mortgage amount NIS (ln)	-0.104**	0.901	0.871	0.933
Loan-to-value ratio (LTV, %)	0.004**	1.004	1.003	1.006
Family size, persons	0.001	1.002	0.988	1.015
Neighborhood socioeconomic status (SES)	0.000	1.000	0.995	1.005
Year 2011 dummy	-0.164**	0.848	0.806	0.894
Environmental variables:				
NOx ,ppb	0.044**	1.045	1.042	1.048
O_3,ppb	-0.004	0.996	0.991	1.000
PM_{10},ppb	0.033**	1.033	1.023	1.044
$PM_{2.5}$,ppb	0.869**	1.055	1.050	1.060
SO_2,ppb	0.112**	1.119	1.093	1.145
D_road, m[7]	$8.89E^{-05}$	1.000	1.000	1.000
Palestinian Authority (PA) (yes/no)	0.087	1.091	0.998	1.193
D_north, km (ln)	0.029	1.029	0.984	1.076
D_gaza, km (ln)	-0.061	1.029	0.984	1.076
No. of cases	88,655			
X^a	701.594			
-2 Log likelihood	245905.865			

Notes: *Method: Cox proportional hazards model; independent variables: MA event (Yes = 1, No = 0), and duration of the MA event in months; all explanatory variables are included. HR = proportional hazards ratio; * indicates a 0.05 significance level; ** indicates a 0.01 significance level (two-tailed). X^a is the goodness-of-fit statistic.*

Table 6 shows the observed values of the analyzed variables in each of the clusters. The values of the variables range over a wide interval—from 28.21% (SD = 9.27) in the first LTV cluster to an average of 87.93% (SD = 5.42) in the third LTV cluster. Similarly, the net monthly income in NIS (ln) is 9.53 (SD = 0.53) in the first income cluster and 13.10 (SD = 0.48) in the third income cluster, and the average family size is 3.56 persons (SD = 2.01) in the first family-size cluster and 12.43 (SD = 0.38) in the third cluster.

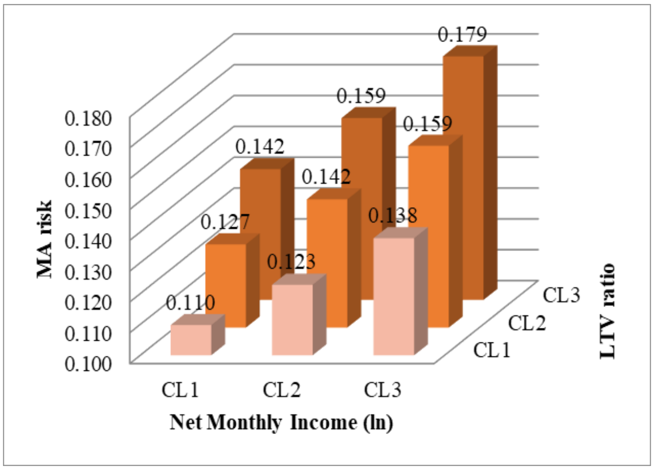
[7] *Although the road proximity variable emerged statistically insignificant (p>0.1), we tested a possibility whether it becomes significant when it is included without specific pollutant measures. As the results of the analysis showed, the road proximity variable did not emerge significant, thus indicating that it cannot serve as a useful substitute for direct air pollution measurements. The model incorporating road proximity but excluding air pollution variables are not reported in the following discussion for brevity's sake.*

Table 6. *Selected Descriptive Statistics of Research-Variable Clusters*

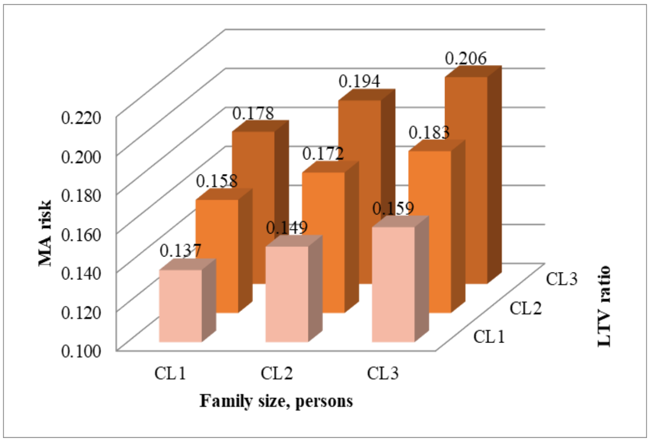
Variable	Cluster #	Cluster definition	Mean	SD
Loan-to-value (LTV) ratio, %	CL1	Low	28.21	9.27
	CL2	Medium	60.78	9.29
	CL3	High	87.93	5.42
Net monthly income, NIS (ln)	CL1	Low	9.53	0.53
	CL2	Medium	11.34	0.48
	CL3	High	13.10	0.48
Family size, persons	CL1	Small-to-medium	3.56	2.01
	CL2	Medium-to-large	8.82	1.20
	CL3	Large	12.43	0.38

Source : *Own study.*

Figure 2. *MA risk estimates for different combinations of socioeconomic attributes of mortgage borrowers*



A



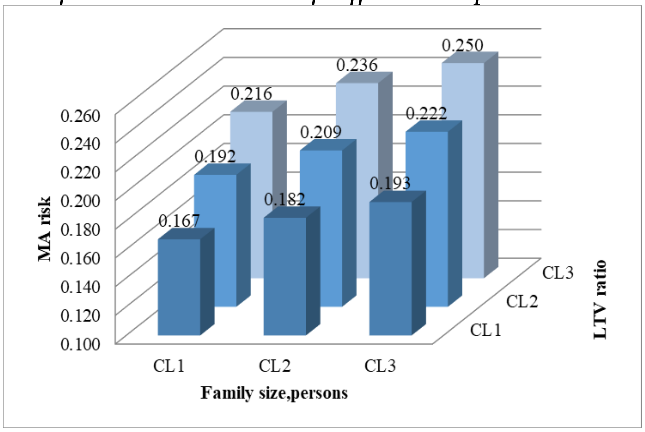
B

A: Loan-to-value (LTV) ratio (%) vs. net monthly income, NIS (ln); B: LTV (%) vs. family size (persons).

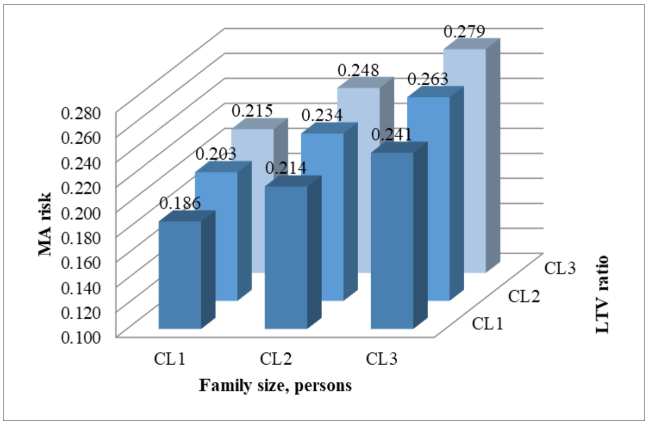
Cluster breakdown: Net family income in NIS: CL1 = low income, CL2 = medium income, CL3 = high income (see Table 2 for cluster breakdown values); Family size: CL1 = small-to-medium family, CL2 = medium-to-large family, CL3 = very large family (see Table 2); LTV: CL1 = low LTV, CL2 = medium LTV, CL3 = high LTV (see Table 2). *Notes*: MA risk estimates are calculated on a continuous probability scale, ranging from 0 (improbable event) to 1 (highly probable event), using Model 1 (Table 1), which does not include air pollution variables. All the mortgage transactions are divided into clusters using the hierarchical clustering method, with the IBM SPSS™v.25 software. The values of the target variables were set to the cluster means (Table 3), while the values of all the other variables were set to their list-wise averages (Table 1).

Using this division into clusters, we next estimated the relative risks of MA for each combination of the subject variables. Figures 2-4 show the MA risk estimates calculated on a continuous probability scale, ranging from 0 (an improbable event) to 1 (a highly probable event). The estimates were calculated using Model 1 (Table 3), which does *not* include air pollution variables. For these calculations, the values of the target variables were set to the cluster means (Table 6), while the values of the other variables were set to their list-wise averages (Table 1).

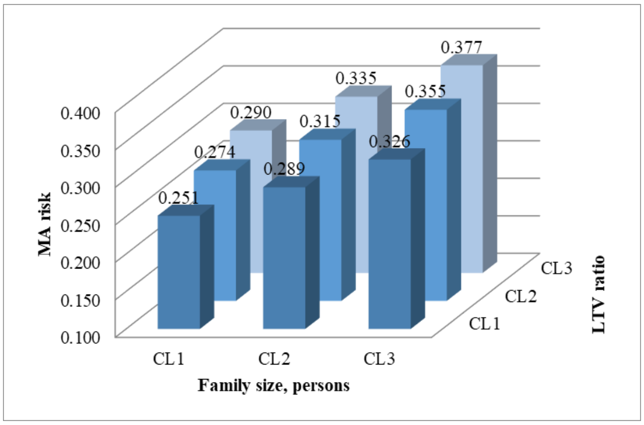
Figure 3. *MA risk estimates for different cluster combinations of LTV vs. family size, adjusted to account for the contribution of different air pollution variables.*



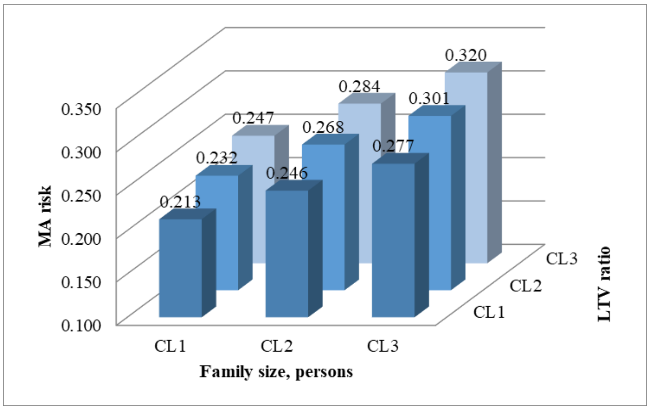
A



B



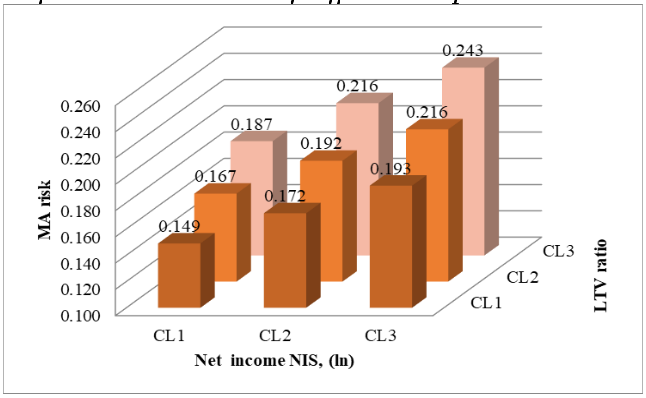
C



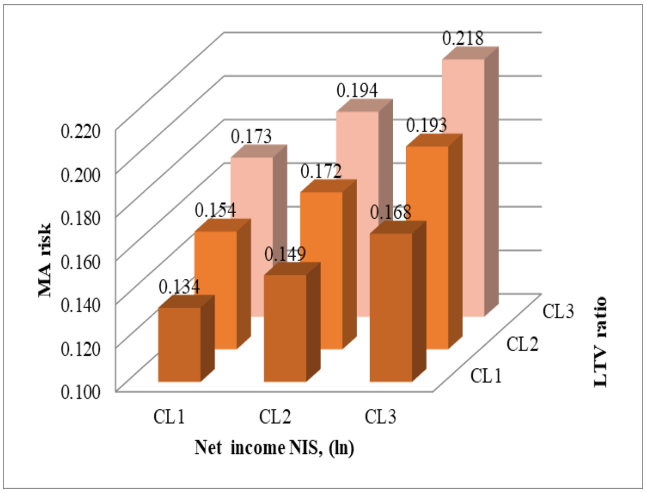
D

A: O_3; B: SO_2; C: PM $_{2.5}$; D: PM_{10}. ***Notes:*** *See comments on Figure 2. The levels of individual air pollutants are set to their countrywide averages (Table 1).*

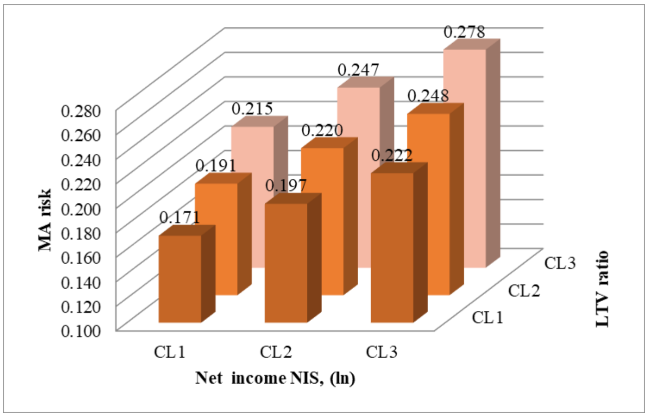
Figure 4. *MA risk estimates for different cluster combinations of LTV vs. net income NIS (ln), adjusted for the contribution of different air pollution variables.*



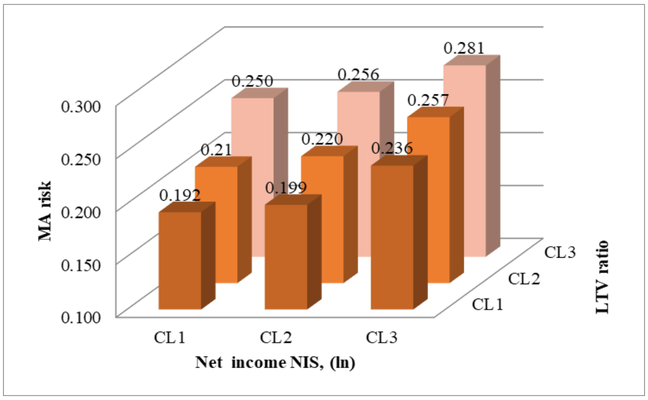
A



B



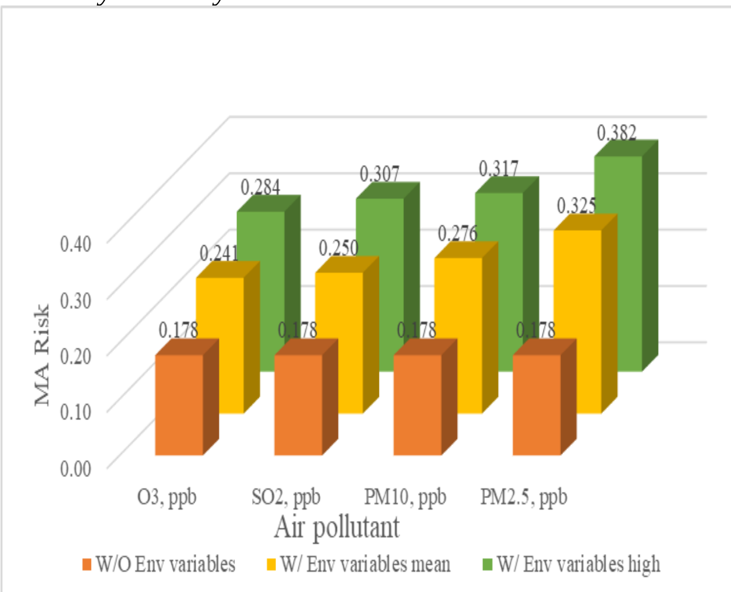
C



D

A: O_3; B: SO_2; C: PM $_{2.5}$. D: PM_{10}. ***Notes:*** *See comments on Figure 2. The levels of individual air pollutants are set to their countrywide averages (Table 1).*

Figure 5. *Summary of MA risk estimates for different levels of air pollution variables covered by the analysis.*



Notes: *The values are calculated using Models 1–2 (Table 2). The values of all non-air-pollution variables used to calculate the risk levels were set to their countrywide means (see Table 1), while the values of the air pollution variables were set to zero (orange columns), the mean value (yellow columns), and the maximal value (green columns) observed for the corresponding air pollutants countrywide (Table 1).*

As Figures 2-4 show**,** the estimated MA risk increases from 0.110 in the first LTV-income cluster combination to 0.179 in the third one. Similarly, the MA risk estimates range from 0.137 in the first LTV-family size cluster combination (small LTV and small family size) to 0.206 (large LTV and large family size) in the third cluster. Figure 3C indicates that adding air pollution variables in all combinations of clusters increases the MA risk to 0.251–0.377, depending on the type of air pollutant. The highest increase in MA risk is observed for the pollutants $PM_{2.5}$ and PM_{10} (Figures 3C–3D). Figure 5 summarizes the different risk levels caused by different air pollutants.

6. Discussion and Conclusions

The present study estimates environmentally-adjusted MA rates for different socioeconomic groups of borrowers in Israel, using data from 2010–2011. For the analysis, individual mortgage records were obtained from a national mortgage database, maintained by a leading commercial bank. For each mortgaged property, several environmental and geographic attributes were estimated, including annual air pollution averages, proximity to main roads and proximity to high-security risk areas, such as the border with Lebanon in the North and the border with the Gaza strip in the south. Based on these data, proportional hazards models were used to identify factors that significantly affect the MA risk.

Studies of MAs commonly include predictors, such as age, education, net income, family size, interest rate, total mortgage, income-to-payment rate, mortgage maturity, LTV, current LTV (Gerlach-Kristen & Lyons, 2018). The present study covers most of these variables, including age, education, total mortgage, LTV rate, family size, and net family income. Although other variables, such as current LTV and current rate of payment-to-income, would be desirable, information on these variables is not recorded in the commercial bank database used in the analysis. In particular, the payment-to-income (PTI) rate is determined by the bank at the time of mortgage issuance only and is not reevaluated thereafter. The same with the current LTV, which is also estimated by an appraiser only once, at the time of mortgage issuance. Importantly, the survival model based on Cox regression and used in the paper, take under the consideration the time factor, in contract to many studies based on simple logistic regressions (see e.g., Borochov et al., 2019), which ignore that factor.

Most of the air pollution variables we analyzed (i.e., SO_2, O3, $PM_{2.5}$, PM_{10}, and NO_X) were found to be statistically significant predictors of the incidence of MA ($p<0.01$). Therefore, the model that incorporates these variables was found to perform better than the model based only on socioeconomic characteristics of the borrowers and loan attributes. This validates our research hypothesis that the MA risk is affected not only by the individual characteristics of the borrowers, but also by the environmental condition of the area in which the mortgaged property is located (**H_1**).

These results are similar to the results of other studies on MA risk, which show that property location may influence MA risk. Thus, Rauterkus, Thrall, and Hangen (2010), who incorporated the "home efficiency" variable into their model, defined as the existence of close-to-home facilities and infrastructures, revealed that location efficiency is an important factor in predicting MA, because, in highly efficient locations, vehicle fees are lower and home values are maintained, thereby enabling borrowers to avoid foreclosure.

In a separate study, Kaza *et al.* (2016) found that the transportation fees of location efficiency have a statistically significant, but substantively small, impact on the default risk. Pivo (2014) included the walkability factor, determined by walk-score rates to different neighborhood facilities, and showed that the walkability reduces MA risk. In another study, Been *et al.* (2011) found that the neighborhood's physical characteristics and health condition are significant predictors of MA risk, especially among low-income families. However, Noris and Winstone (2011), who included subjective assessments of neighborhood noise, air pollution, the lack of access to recreational or green areas, water quality, crime, and street littering as potential predictors for MA rates, found none of these factors statistically significant.

Compared to these studies, the present research is novel in several aspects. To the best of our knowledge, there have been no previous studies that attempt to calculate environmentally-adjusted risk estimates of MAs for different socioeconomic groups of borrowers. Only one study, by Borochov *et al.* (2019), assessed the effect of various environmental factors on MA risk, using binary regression models. However, these models are insufficiently robust, because they do not take the duration of the period between the mortgage issuance and the mortgage failure into account.

The results of the present analysis may be useful to several groups of users — borrowers, insurance companies, lenders, and government agencies. In particular, individual borrowers can reduce the risk of MA before committing to a high long-term mortgage, by taking into consideration not just economic factors, but also environmental constraints, such as air polution. Lenders can use our assessments to estimate the premium for individual mortgages, while policy-makers can use the knowledge about the MA-related consequences of environmental exposure to promote environmental improvement plans.

According to the Pigouvian tax theory, in the presence of negative externalities and given the appropriate convexity conditions, an efficient allocation of resources can be achieved by levying taxes on commodities that generate external effects, such as e.g., air pollution (Carattini *et al.*, 2018). As the results of the present study point out at a significant negative effect of air pollution on the ability of mortgage borrowers to finance their mortgages, a Pigouvian tax can be imposed on polluting industries and motor-traffic owners, with collected taxes being earmarked to reduce mortgage rates in polluted areas. Such a tax can stimulate polluting companies to reduce pollution and stimulate private households to travel less by private transport, while opting for public transportation, wherever possible. Both measures can result in a cleaner and healthier environment while increasing the financial resilience of mortgage borrowers.

In conclusion, we shall emphasize three main novelty aspects of the present study. First and foremost, it suggests an empirical approach of adjusting MA risk estimates to account for environmental attributes of residential properties (such as air pollution and proximity to high security-risk areas) at the time of mortgage issuance, which are not captured by traditional MA risk-assessment models. Second, the study shows that borrowers' and mortgage attributes (such as net monthly income, family size and LTV ratio) tend to affect different groups of borrowers asymmetrically, with the highest risk of MA observed in large, high income families, which took high LTV mortgages. The study also demonstrates the utility of adding air pollution variables to the list of MA risk-predictors, which helps to introduce significant information, not captured by other observables, such as age of the borrower, family income, LTV ratio, and others.

It should be noted, however, that the present study covers a relatively short period of two years, for which mortgage records were available. Moreover, although the data records that were available to the researchers cover a relatively large sample size (more than 90,000 records), these data are limited to one country and to records from one commercial bank. As local home-ownership markets are rooted in the local culture and banking regulations, our findings are definatelly time- and place-specific, and local conditions in other areas may influence the MA risk differently. Further studies, covering larger time frames and other country-specific data, are therefore needed to confirm the generality of our findings.

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