Air Pollution and Joint Decision:
Evidence from Divorce Records*

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Abstract

We provide novel evidence on how air pollution affects high-stakes joint decisions. Using administrative data of divorce records in a provincial capital in China from 2016 to 2019 and exploiting thermal inversions as an instrumental variable for air pollution, we find that a one standard deviation increase in air pollution in a county per week leads to 0.27 standard deviation more divorce cases. The pollution effects on divorce are mainly driven by couples with relatively high levels of average education and couples with similar education. Our findings show that air pollution exposure is an influential incidental factor for divorce decisions, and bad mood and impulsivity may be important channels.

Keywords: Air pollution, joint decisions, divorce, behavior bias

JEL Classification: D70, D91, J12, Q51, Q53

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1 Introduction

Over the past decades, a growing body of economics literature has documented the health and non-health impacts of air pollution (see reviews by Graff Zivin and Neidell (2013) and Aguilar-Gomez et al. (2022)). One strand of literature has studied how air pollution affects decision-making, because air pollution not only affects respiratory and cardiovascular functioning, but also has large impacts on the brain and central nervous system, which could further impair cognitive function and alter emotional states, such as inducing more aggravation and impulsivity (Aguilar-Gomez et al. 2022). These studies have documented that air pollution affects strategic decision-making in chess tournaments (Kunn et al., 2022), voting (Bellani et al. 2021), crime (Burkhardt et al. 2019, Bondy et al. 2020, Herrnstadt et al. 2021), demand for health insurance (Chang et al. 2018), and professionals' trading and forecasting in the financial market (Huang et al. 2020, Dong et al. 2021, Li et al. 2021). However, previous studies have focused only on sole decision-making (i.e., decisions made by the individual or the party itself). To date, no studies have focused on joint decision-making.

Understanding how pollution affects joint decision-making is important for at least two reasons. First, many real-world decisions are made jointly, such as management decisions among board members, journal and conference submissions among collaborators, and marriage and divorce. Second, joint decision-making typically involves at least two individuals/parties, and thus the process could be different from sole decision-making because of spillover, negotiation, and bargaining. This paper documents the short-run effects of air pollution on people's divorce decision, which is clearly a joint decision and arguably one of the highest-stake decisions. To the best of our knowledge, this paper is the first to study how pollution affects the joint decision-making process.

Specifically, we use administrative data of divorce records in a provincial capital in China from 2016 to 2019 and exploit thermal inversions as an instrumental variable (IV) for air pollution, a common IV used in the literature (Arceo et al., 2016; Fu et al., 2021; Chen et al., 2022). We find that a one-unit increase in air quality index (AQI) leads to 0.21 additional divorce cases in the county per week, which represents about a 0.5% increase compared with the sample mean. The effects are economically meaningful—a one standard deviation increase in air pollution would lead to 0.27 standard deviation (or 13.9%) more divorce cases.

We then discuss the potential mechanisms that air pollution exposure triggers divorce decisions. Previous studies have shown that people are less happy and have worse mental health on heavily polluted days (Zhang et al. 2017, Zheng et al. 2019). On the other hand, pollution could damage the brain and central nervous system, impair cognitive functions, and alter emotional states, such as inducing more aggravation and impulsivity (Aguilar-Gomez et al. 2022). Although we cannot directly test these channels due to data limitation, previous research has suggested that these "behavioral bias" effects could be important channels.

Given our unique setting of joint decision-making, we can investigate how pollution effects change with the demographic characteristics of couples. We find that the pollution effects on divorce are mainly driven by couples with relatively high level of average education, who have better outside options, rather than couples with lower level of education. In addition, the pollution effects on divorce are mostly driven by couples with similar education, who may have similar outside options and lower negotiation costs, but not couples with relatively different education levels. These results indicate that air pollution exposure is an influential incidental factor for divorce decisions, as the effects of air pollution on divorce are pronounced for couples with lower negotiation costs and better outside options—which suggests higher likelihood of transformation from bad mood and impulsivity to divorce. On the other hand, we do not find significant difference for couples with different levels of age difference. Instead, the pollution effects are pronounced for most age cohorts, suggesting that our findings are not driven by certain age groups.

Our paper contributes to a large and growing body of literature on understanding the social and economic costs of air pollution. Our results show that the effects of air pollution exposure on joint decisions are very pronounced, and the effects vary within different households, which have important implications for understanding pollution effects with social interactions. Our paper also joints into the broad literature on behavior bias, particularly on the role of incidental factors in high-stakes decisions (see Lerner et al. (2015) for a review).[1] Lastly, this paper contributes to an emerging literature on understanding the drivers of marriage market, an important determinant of human capital investments, risk-sharing opportunities, and fertility outcomes (Tertilt, 2005; Field and Ambrus, 2008; Bertrand et al., 2015; Chiappori et al., 2018; Corno et al. 2020; Serra-Garcia 2022). To the best of our knowledge, this study is the first that shows ambient environment plays a role in divorce decisions. Our findings show that small incidental factors, such as air pollution, can be influential in divorce decisions and family stability as well.

2 Data

2.1 Divorce Data

[1] Previous studies have documented that important decisions may be affected by small and seemingly unrelated factors, including temperature (Heyes and Saberian 2019) and unexpected local football game outcomes (Eren and Mocan 2018) for judges, rainfall (Gomez et al. 2007, Meier et al. 2019) and air pollution (Bellani et al. 2021) on the election day for voters, as well as weather on campus visit days for prospective students (Simonsohn 2010).

Typically, there are two ways to get divorced in China. The first way is divorce by agreement or by mutual consent. If both parties agree to get divorced, then they can go to the local Civil Administration Department and file the application. They often do not have to make appointments in advance. There was no waiting time requirement before year 2020, and the divorce registration process could be completed within one day.[2] The second way is divorce by litigation, which often happens when one party does not agree, so the other party file a litigation through a court. In China, the second way is considerably rare in practice and often takes at least one to two years. Divorce by agreement is the most common practice of divorce and accounts for 80%–90% of the total divorce cases in China.[3]

We obtain administrative data of the divorce registration records (divorce by agreement) in City W from 2016 to 2019. City W is a provincial capital with 13 counties/districts and has a population of over 10 million.[4] Our data contain the universe of divorce registration records in City W, with information on the week of the divorce registration, county of registered residence (*hukou*) for both parties, and their demographic characteristics, including age and education. We aggregate divorce registration records to county–week level. There are 13 counties and 208 weeks in our sample, which leads to 2,704 observations in total.

One potential issue is to determine the county of pollution exposure for the couple. Although we do not have information on their exact living address, we are able to infer their living counties and, thus, their pollution exposure, given that the divorce registration must be in the *hukou* county of one party. There are three cases. First, when both parties' *hukou* counties are the same and are in City W, the county is assigned as the living county.[5] This case accounts for 48.7% of observations. Second, when one party's *hukou* county is in City W, and the other party's *hukou* county is in other cities or provinces, the county in City W is assigned as the living county because it is relatively costly to travel and get divorced in the other city or province. This case accounts for 29.8% of observations. Lastly, when both parties' *hukou* counties are different but both are in City W, we are unable to infer the living county. Thus, these observations are dropped. This case accounts for 21.5% of observations. We use the first two cases as our baseline measure but also use the first case only as a robustness check.

[2] China revised its divorce practice after 2020, and couples need to wait for 30 days of "cooling-off" period before the completion of the divorce registration process.
[3] For example, there are 3.81 million and 4.05 million divorce cases by agreement in 2018 and 2019, respectively, and 0.65 million and 0.65 million divorce cases by litigation in 2018 and 2019, respectively.
[4] China has three administrative levels: province (2-digit code), prefectures/cities (4-digit code), and counties/districts (6-digit code). City W is a 4-digit level. The 13 counties/districts are 6-digit level. Given that counties and districts are in the same administrative level, we use the two terms interchangeably.
[5] An implicit assumption is that the couple actually lives in the *hukou* county. This case is true for most Chinese people because many living attributes, such as children's education and medical care, are associated with *hukou*.

2.2 Air Pollution Data

We obtain pollution data from the official website of the Ministry of Environmental Protection of China. Since 2013, the ministry has been publishing real-time air quality index (AQI) and six specific air pollutants, namely, $PM_{2.5}$, PM_{10}, sulfur dioxide (SO_2), ozone (O_3), nitrogen dioxide (NO_2), and carbon monoxide (CO), for over 1,400 stations.[6] We use the inverse-distance weighting (IDW) method to convert station-level pollution data to county (Deschênes and Greenstone 2011) with a radius of 200 km.

We choose AQI as our primary measure of air pollution because different pollutants are often highly correlated, and isolating the effects of a single pollutant is difficult, even if thermal inversion is used as instrumental variable (Arceo et al. 2016, Fu et al. 2021). This situation is also consistent with previous studies on air pollution effects on decision-making in other settings (Chang et al. 2018, Huang et al. 2020, Dong et al. 2021, Li et al. 2021). We also present the results when we use $PM_{2.5}$ and PM_{10}, which are two major air pollutants in China.

2.3 Thermal Inversion Data

We obtain thermal inversion data from the MERRA-2 database released by NASA.[7] The data report air temperatures every 6 hours at 42 vertical layers from 110 m to 36,000 m within 50 km × 60 km grids. We follow Fu et al. (2021) and downscale the 50 km × 60 km grids to 10 km × 12 km grids using the bilinear interpolation method and aggregate to the county level thereafter. We likewise follow Arceo et al. (2016) and Fu et al. (2021) and define a thermal inversion if the temperature in the second layer (320 m) is higher than that in the first layer (110 m) for each six-hour period. We also check the robustness by defining a thermal inversion if the temperature in the third layer (540 m) is higher than that in the first layer (110 m). In the baseline, we use the total number of thermal inversions (ranging from 0 to 4 in each day) in a week, but the results are robust when using alternative measures, including number of inversion days.

2.4 Weather Data

We obtain weather data from the National Meteorological Information Center of China. It reports daily temperature, precipitation, relative humidity, wind speed, sunshine duration, and barometric pressure from

[6] Air quality index (AQI) captures the overall air pollution concentration, and air quality is classified into several categories: excellent ($AQI \leq 50$), good ($50 < AQI \leq 100$), lightly polluted ($100 < AQI \leq 150$), moderately polluted ($150 < AQI \leq 200$), heavily polluted ($200 < AQI \leq 300$), and severely polluted ($AQI > 300$).
[7] We briefly explain what a thermal inversion is in Section 3.

over 800 weather stations. We again use the IDW method to convert station-level data to county-level weather data (Deschênes and Greenstone 2011) with a radius of 200 km.

3 Empirical Strategy

To estimate the effects of air pollution on divorce decisions, we exploit the panel structure of the data using the following specification:

$$Divorce_{cymw} = \beta_0 + \beta_1 AQI_{cymw} + \theta X_{cymw} + \mu_{cy} + \gamma_m + \rho_w + \varepsilon_{cymw}, \quad (1)$$

where $Divorce_{cymw}$ is the total number of divorce cases in county c in year y, month m, and week w; and AQI_{cymw} is the air quality index, which measures air pollution level in the same county–year–month–week cell; X_{cymw} denotes a set of control variables, including weather controls (i.e., weekly average of temperature, precipitation, relative humidity, wind speed, sunshine duration, and pressure) and calendar week characteristics (i.e., a set of dummy variables for the number of workdays in the week, accounting for statutory holiday adjustments; a dummy variable for Chinese Lunar New Year weeks; and a dummy variable for National Day Holiday weeks). We also include county-by-year fixed effects μ_{cy}, month fixed effects γ_m, and week-of-month fixed effects ρ_w to control for county-year invariant confounders and potential time trends and seasonality. Robust standard errors are used in the baseline (identical to clustering at county-week level, following Chang et al. 2018), and the results are mostly unchanged using alternative clustering methods.

Despite the above fixed-effect specification with high-frequency data, there could still be unobserved time-varying confounding factors, such as economic activities and measurement error (Deryugina et al. 2019). Therefore, we implement an instrumental variable approach that relies on variations in thermal inversion as exogenous shocks to local air pollution level. Thermal inversion is a meteorological phenomenon, in which a mass of warmer, less dense air moves above a cooler, denser air mass, trapping dust and pollutants near the ground and increasing air pollution. Given that thermal inversion is a meteorological phenomenon, it is less correlated with economic activities. In addition, it does not pose health risks conditional on weather variables. This identification strategy is frequently used in the environmental economics literature, including Arceo et al. (2016), Sager (2019), Deschênes et al. (2020), Fu et al. (2021), and Chen et al. (2022), to estimate the effects of air pollution on various outcomes. Specifically, we estimate the following 2SLS models:

$$AQI_{cymw} = \alpha_0 + \alpha_1 ThermalInversion_{cymw} + \theta X_{cymw} + \mu_{cy} + \gamma_m + \rho_w + \varepsilon_{cymw}, \quad (2)$$

$$Divorce_{cymw} = \beta_0 + \beta_1 \widehat{AQI_{cymw}} + \theta X_{cymw} + \mu_{cy} + \gamma_m + \rho_w + \varepsilon_{cymw}, \quad (3)$$

where $ThermalInversion_{cymw}$ is the number of thermal inversions in county c in year y, month m, and week w.

4 Results

4.1 Main Results

Table 1 presents the summary statistics. Each county-week has an average of 43.5 divorce cases, and the number of divorce cases ranges from 0 to 132 in a week. When only considering couples with the same *hukou* county in City W (the first case as described in Section 2.1), the number of divorce cases ranges from 0 to 93, with an average of 27 cases. We also report the summary statistics by education.[8] When dividing the sample based on the couples' average education, there are 7.7, 22.3, and 13.5 divorce cases for couples with high, middle, and low levels of average education, respectively. When dividing the sample based on the couples' relative education, there are 29.3 divorce cases for couples with the same level of education, while only 7.9 and 6.3 divorce cases for couples with more educated males and females, respectively. The average AQI in our sample is about 76.8, which corresponds to the "good" level of air quality. The average $PM_{2.5}$ concentration is 49.65 $\mu m/m^3$, which is 10 times higher than the new WHO standard of 5 $\mu m/m^3$. The average PM_{10} concentration is 81.88 $\mu m/m^3$, which is 5 times higher than the new WHO standard of 15 $\mu m/m^3$. The total number of thermal inversions in a week is 6.13 on average, indicating that the probability of incurring a thermal inversion is 6.13/(7 $\times$ 4) = 22%.

Table 2 shows our main results. Panel A presents the first-stage results of our 2SLS specification using thermal inversion as instrumental variable (Equations (2) to (3)). The results show that thermal inversion is a powerful predictor of air pollution concentration: one additional thermal inversion in a week increases the weekly average AQI by 1.33 units, with a first-stage KP-F statistics of 162.0, which is much higher than the Stock-Yogo critical value of 16.38 (Kleibergen and Paap 2006).

Panel B presents the second-stage results of our 2SLS specification. The 2SLS coefficient, as shown in column (1), suggests that a one-unit increase in AQI leads to 0.21 additional divorce cases in the county-week, which is about a 0.5% increase compared with the sample mean (or 0.01 standard deviation).

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[8] The educational attainment in our data is classified into four groups: 1 - middle school or less (below or equal to compulsory schooling); 2 - high school or equivalents, without bachelor's degree (including technical colleges); 3 - bachelor's degree, and 4 - master's degree or above. We divide the sample based on the average and relative education of the couples. Detailed variable definitions and classifications are explained in Section 4.3.

Thereafter, we use several alternative dependent variable measures to illustrate the robustness of our results. In column (2), we use inverse hyperbolic sine transformation of the number of divorce cases as dependent variable to ease the elasticity interpretation of the coefficients.[9] The results suggest an estimated elasticity of 0.5% for the 2SLS specification, which is similar to our baseline results. Our baseline measure on divorces using couples within the same *hukou* county in City W and couples with one party's *hukou* county in city W and the other party's *hukou* county in other cities or provinces (the first two cases described in Section 2.1). In column (3), we use the number of divorce cases for couples within the same *hukou* county in City W only (the first case described in Section 2.1). The results are very similar, indicating that our results are unlikely to be biased by different measurement on divorce cases.

For comparison, we present our OLS estimates (Equation (1)) in Panel C. Column (1) shows that a one-unit increase in AQI is associated with 0.044 additional divorce cases in the county-week, a substantially smaller point estimate compared with our 2SLS results, or 0.1% increase compared with the sample mean. The results are similar using alternative dependent variable measures in columns (2) and (3). Overall, the OLS estimates indicate a strong positive association between air pollution and divorce cases, but the magnitude is markedly smaller than the 2SLS estimates. This result indicates the importance of instrumenting air pollution, which could correct for omitted-variable bias and measurement error (Deryugina et al., 2019).

Overall, our main results indicate a strong causal relationship between air pollution and divorce decisions—more people tend to get divorced because of higher air pollution in a week. The effect is also economically meaningful—a one standard deviation increase in air pollution level leads to 0.27 standard deviation (13.9%) more divorce cases. Even though severe air pollution in a week is only a negligible factor for a life-time decision, it appears to be influential for people's actual decisions.

Although we cannot directly test channels through which air pollution increases divorce cases due to data limitation, we briefly discuss the potential mechanisms. Numerous previous studies have shown that people are less happy and have worse mental health on heavily polluted days (Zhang et al. 2017, Zheng et al. 2019), and bad mood could induce aggressive behavior and impulsivity, intra-household conflict, and, in the extreme form, divorce. Meanwhile, air pollution could directly affect the brain and central nervous system, and further alter emotion states (see Aguilar-Gomez et al. 2022 for a review), which play important roles in decision-making (Lerner et al., 2015).

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[9] The inverse hyperbolic sine function, $IHS(x) = log(x + \sqrt{1 + x^2})$, is approximate to log function that the marginal effects can be interpreted as percentage changes for small changes, but the function is well-defined at 0. This measure is commonly used in the literature (Barreca et al. 2021, Card and DellaVigna 2017).

4.2 Robustness and Additional Results

Table A1 presents the estimation results of a few variants of our baseline 2SLS specification. Column (1) shows our baseline results, which is the same as the bottom panel of column (1) in Table 2. We first test the robustness of the control variables. Our baseline model includes weather controls using the weekly average. In column (2), we calculate 5 quantiles for each weather variable based on county-day level distribution in 2016–2019, and include the number of days within each quantile of the county-week. This non-parametric method enables us to control weather variables in a non-linear way, and the results are not substantially different from our baseline.[10] In column (3), instead of using month fixed effects, we include year-by-month fixed effects to allow different seasonality patterns in different years; point estimates are slightly smaller but still highly statistically significant. In column (4), instead of including week-of-month fixed effects, we use a more saturated model and include week-of-year fixed effects to control for temporal trends more conservatively. The point estimate becomes larger and remain highly statistically significant.

We also test the robustness of clustering standard errors. In columns (5) and (6), we cluster the standard errors at the county and week levels, respectively, instead of using robust standard errors in our baseline model. The results are mostly unaffected. Lastly, we test the robustness of our measures of thermal inversion and air pollution. Our baseline inversion measure is the total number of inversions in a week. In column (7), we use number of days having at least one thermal inversion in a week, and the results are robust. In column (8), we return to the baseline inversion measure but change the inversion construction using the layers 540 m and 110 m, rather than 320 m and 110 m, in the baseline. Again, our results are robust. In columns (9) and (10), we report the estimates for $PM_{2.5}$ and PM_{10} respectively. The results show that a one standard deviation increase in $PM_{2.5}$ (PM_{10}) leads to 0.37 (0.21) standard deviation or 19.2% (10.7%) more divorce cases. These effects are large and economically meaningful as well. Note that isolating the effects of a single pollutant is difficult, even when using thermal inversion as an instrumental variable (Arceo et al. 2016, Fu et al. 2021). Therefore, we choose AQI as our primary measure of air pollution because different pollutants are often highly correlated. Thus, our results are better interpreted as air pollution impacts more broadly rather than a specific pollutant.

We also examine the dynamics of air pollution on the divorce decision. Given that including leads and lags of air pollution in our 2SLS specification would suffer from weak identification problem, we directly estimate the reduced-form regression, that is, the effects of thermal inversions (with leads and lags, all

[10] Given that our observation is at the county-week level, we do not have a large sample size. Therefore, we do not include the exhaustive non-parametric weather controls in our baseline specification and further heterogeneous effect analysis.

estimated jointly in one regression) on divorce decisions. The coefficient estimates for past, contemporaneous, and future thermal inversion effects are plotted in Figure 1.

Similar to our baseline results, the contemporaneous effect is large and highly statistically significant after including leads and lags of thermal inversions, and the magnitude barely changes as well. Note that our divorce data are aggregated at week level, rather than day-to-day level. Hence, the contemporaneous effect (i.e., the same week effect) already reflects some intermediate and lagged effects (several days). In contrast, the estimated effects for past thermal inversion are mostly small and statistically insignificant. In addition, the estimated effects for future thermal inversion, which are essentially “placebo” treatment effects, are also small and insignificant. These results reassure our main findings and help us understand the dynamics of pollution effects. When we sum up all coefficients over the five-week window (the contemporaneous effect and lagged effects), the cumulative effect is 0.45, which is approximately 65% larger than the point estimate of the contemporaneous effect, and it is statistically significant at 1% level. This result implies that the effects of thermal inversion on divorce are not offset because of temporal displacement, and it is indeed influential on divorce decisions.

We also examine the potential non-linearity of the effects of air pollution on divorce. Again, we focus on the reduced-form effects because of weak identification problem. In particular, we include variables of the number of days with 1 thermal inversion event in the week, number of days with 2 thermal inversion events in the week, and number of days with 3 to 4 thermal inversion events in the week in the regression.[11] The results are presented in Table A2. As shown in column (1), having one additional day with 1 thermal inversion event in the week increases the number of divorce cases by 0.41 units, while having one additional day with 3 to 4 thermal inversion events increases the number of divorce cases by 1.11 units. Indeed, having additional days with higher concentration of thermal inversions shows much larger effects on divorce. This result indicates that the effects of air pollution on divorce are potentially non-linear, with larger effects under higher concentration of air pollution.

4.3 Heterogeneous Effects by Couple Characteristics

In this section, we present the heterogeneous effects of air pollution on divorce by distinguishing divorce cases from people with different characteristics. Table 3 presents the effects on groups with different

[11] Note that the number of thermal inversions in a day takes integer values from 0 to 4 because inversions are determined within each 6-hour period. The baseline group (i.e., number of days with no thermal inversion events) is omitted in the regression because of collinearity. In our sample period, 42% of county-day level observations have no thermal inversions, 31.5% of the observations have 1 thermal inversion in the day, 23% of the observations have 2 thermal inversions in the day, and 3.5% of the observations have 3–4 thermal inversions in the day.

educational attainment. The educational attainment in our data is classified into four groups: middle school or less; high school or equivalents, without bachelor's degree (including technical colleges); bachelor's degree; and master's degree or above. In columns (1) to (3), we first split the divorce records based on the couples' average education. Given that there are four possible education levels for each of couple, we transform educational attainment levels to years of schooling and divide the sample thereafter based on the average years of schooling.[12] The results indicate that the pollution effects are mostly driven by couples with high and middle levels of education, whereas couples with low levels of education show small and insignificant effects. These differential effects could come from differential sensitivity to air pollution in the outcome of bad mood and impulsivity, or differential likelihood of transformation from bad mood and impulsivity to divorce. However, previous findings have suggested that people with low levels of education are *more*, rather than *less*, affected by air pollution in terms of happiness and mental health (Zhang et al. 2017), so it is possible that our results are mostly explained by the latter explanation. On the other hand, couples with lower levels of education are likely to have worse outside options, and thus are less likely to be triggered by the incidental factor of air pollution.

We then divide the sample into three groups based on the relative education level between the couples in columns (4) to (6): men and women have the same education level, men have higher education, and women have higher education. We find that pollution effects on divorce are mainly driven by couples with similar education and not by couples with relatively different education. As there is no specific reason on why sensitivity to air pollution would depend on *relative* education, these differential effects are more likely from differential likelihood of transformation from bad mood and impulsivity into divorce. Moreover, couples with similar education are likely to have similar outside options. Hence, negotiations through bargaining could be easier. Given that mutual consent of divorce is often associated with negotiation and bargaining for the divorce settlement, lower negotiation and bargaining cost would make the incidental factor of air pollution more influential in divorce decisions.

We additionally present the results on the non-linearity of the pollution effects by education in columns (2) to (7) of Table A2. The overall pattern of these results is similar to the results in column (1) of Table A2 and Table 3, that the effects are larger with worse air quality, and the effects are still driven by couples with higher levels of education and couples with similar education.

[12] The transformation is as follows: group 1 (middle school or less) - 9 years; group 2 (high school or equivalents) -12 years; group 3 (bachelor's degree) -16 years; and group 4 (master's degree or above) -19 years. Couples with average years of schooling of smaller than 12 years are defined as low overall education. Couples with average years of schooling of [12,16) years are defined as middle overall education. Lastly, couples with average years of schooling of above or equal to 16 years are defined as high overall education.

Table 4 presents the effects on groups with different age combinations. In columns (1) to (5), we divide the sample based on the couples' average age. The results show that the effects of pollution on divorce are smaller and insignificant for couples below 30 years old, who have generally shorter marriage, but are pronounced for older age cohorts. In columns (6) to (10), we divide the sample based on the relative age differences (male minus female) between men and women, and the effects are pronounced for all groups. These results indicate that the effects of air pollution on divorce are present for couples of many different age groups, rather than driven by certain groups of people.

In conclusion, these heterogeneous effect analyses show that the effects of air pollution on divorce are pronounced for couples with lower negotiation costs and better outside options. This result is consistent with the hypothesis that air pollution exposure is an influential incidental factor for divorce decisions. Moreover, the result emphasizes the importance of studying how pollution affects decision-making in a joint framework. This perspective could be different from sole decision-making because of spillover, negotiation, and bargaining between individuals and parties.

5 Conclusion

We provide novel evidence on how a small incidental factor—air pollution—may affect high-stakes joint decisions. Using administrative data of divorce records in a provincial capital in China from 2016 to 2019 and exploiting thermal inversions as an instrumental variable for air pollution, we find that a one-unit increase in AQI leads to 0.21 additional divorce cases in the county per week, which is about a 0.5% increase compared with the sample mean. The effects are economically meaningful—a one standard deviation increase in the air pollution would lead to 0.27 standard deviation more divorce cases (or 13.9% more divorce cases). Our findings show that air pollution exposure may trigger divorce decisions, arguably one of the highest-stake joint decisions in the real world. In addition, our findings on how pollution effects change with the demographic characteristics of the couples show that the pollution effects on divorce are mainly driven by couples with lower negotiation costs and better outside options. This result indicates that air pollution exposure is an influential incidental factor for divorce decisions. Unfortunately, we are unable to fully distinguish between and to test for the potential mechanisms of pollution effects on joint decision-making, although previous studies have suggested that bad mood and increased impulsivity may be one of the important channels. Future research is needed in this area.

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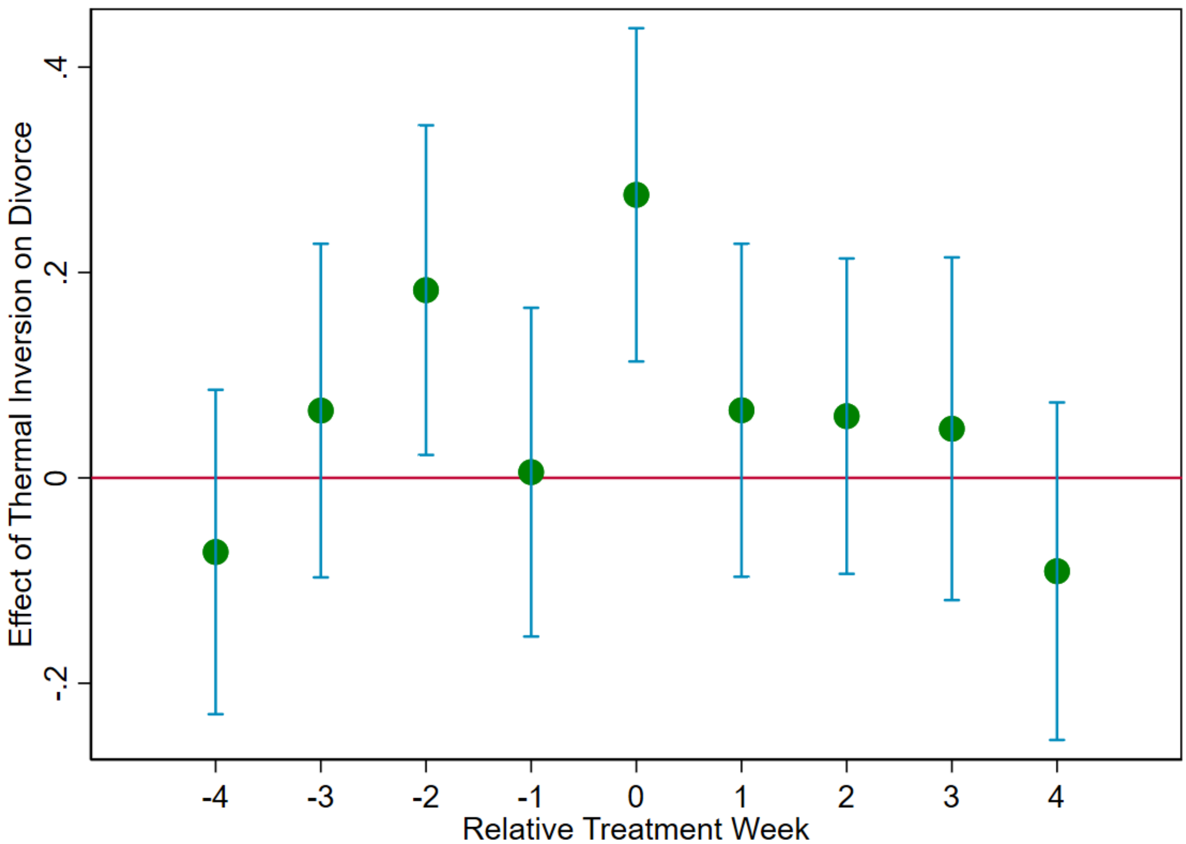
Figures and Tables

Figure 1: Dynamic Effects of Thermal Inversion on Divorce



Notes: This figure plots the estimated effects of lags and leads of thermal inversion on the number of divorce cases. Weather variables (temperature, precipitation, relative humidity, wind speed, sunshine duration, and air pressure) of these weeks, calendar week characteristics, county-by-year fixed effects, month fixed effects and week-of-month fixed effects are controlled in all regressions. Robust standard errors are used. The "-" markers represent bounds of 95% confidence interval.

Table 1: Summary Statistics

	(1) Mean	(2) S.D.	(3) Min	(4) Max
Number of Divorce Cases				
Total Divorce Cases	43.50	22.44	0	132
Couples with the Same *Hukou* County Only	26.99	17.74	0	93
Overall Education: High	7.72	8.29	0	51
Overall Education: Middle	22.30	12.71	0	76
Overall Education: Low	13.48	12.06	0	95
Relative Education: Equal	29.33	15.81	0	99
Relative Education: Male High	7.88	5.59	0	36
Relative Education: Male Low	6.29	4.52	0	30
Air Pollution and Thermal Inversion				
Air Quality Index	76.81	29.04	27.71	173.21
$PM_{2.5}$	49.65	25.28	14.25	137.07
PM_{10}	81.88	32.80	25.23	207.39
Thermal Inversion	6.13	3.80	0	18

Notes: Number of observations=2,704.

Table 2: Effects of Air Pollution on Divorce

	(1)	(2)	(3)
Panel A 2SLS First Stage			
Dependent Variable	Air Quality Index		
Thermal Inversion	1.3324***		
	(0.1047)		
Panel B 2SLS Second Stage			
Dependent Variable	Divorce	Divorce: Inverse Hyperbolic Sine	Divorce: Same County Only
Air Quality Index	0.2087***	0.0047***	0.1903***
	(0.0500)	(0.0012)	(0.0428)
1st-stage KP F-stat	162.0	162.0	162.0
Panel C OLS			
Dependent Variable	Divorce	Divorce: Inverse Hyperbolic Sine	Divorce: Same County Only
Air Quality Index	0.0442***	0.0013***	0.0430***
	(0.0130)	(0.0003)	(0.0114)
Observations	2,704	2,704	2,704
Weather Controls	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Week of Month FE	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Panel A shows the first-stage results of the 2SLS specification, and Panel B shows the second-stage results of the 2SLS specification, which uses the thermal inversion measure as an instrument for the air quality index. Panel C shows the results of the OLS specification. In Panel A, the dependent variable is the air quality index. In Panels B and C, the dependent variable is the number of divorce cases in column (1), the inverse hyperbolic sine of the number of divorce cases in column (2), and the number of divorce cases for only couples with the same *hukou* county in City W in column (3). Weather variables (temperature, precipitation, relative humidity, wind speed, sunshine duration, and air pressure), calendar week characteristics, county-by-year fixed effects, month fixed effects and week-of-month fixed effects are controlled in all columns.

Table 3: Heterogeneous Effects by Education

	(1)	(2)	(3)	(4)	(5)	(6)
	Divorce by Overall Education			Divorce by Relative Education		
Dependent Variable	High	Middle	Low	Equal	Male High	Male Low
Air Quality Index	0.0599***	0.1431***	0.0057	0.1836***	0.0125	0.0127
	(0.0189)	(0.0360)	(0.0302)	(0.0403)	(0.0162)	(0.0150)
Observations	2,704	2,704	2,704	2,704	2,704	2,704
1st-stage KP F-stat	162.0	162.0	162.0	162.0	162.0	162.0
Mean of Dependent Variable	7.72	22.30	13.48	29.33	7.88	6.29
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Week of Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the number of divorce cases by average education of couples in columns (1)-(3), and the number of divorce cases by relative education between couples in columns (4)-(6). All regressions use the 2SLS specification and use the thermal inversion measure as an instrument for the air quality index. Weather variables (temperature, precipitation, relative humidity, wind speed, sunshine duration, and air pressure), calendar week characteristics, county-by-year fixed effects, month fixed effects and week-of-month fixed effects are controlled in all columns.

Table 4: Heterogeneous Effects by Age

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Divorce by Average Age					Divorce by Relative Age Difference				
Dependent Variable	<=30	(30,35]	(35,40]	(40,50]	>50	<=-1	(-1,1]	(1,3]	(3,5]	>5
Air Quality Index	0.0223	0.0602***	0.0280*	0.0360**	0.0623***	0.0331**	0.0545**	0.0534***	0.0240*	0.0437***
	(0.0163)	(0.0205)	(0.0164)	(0.0181)	(0.0163)	(0.0146)	(0.0217)	(0.0191)	(0.0136)	(0.0148)
Observations	2,704	2,704	2,704	2,704	2,704	2,704	2,704	2,704	2,704	2,704
1st-stage KP F-stat	162.0	162.0	162.0	162.0	162.0	162.0	162.0	162.0	162.0	162.0
Mean of Dependent Variable	7.09	11.32	8.03	9.72	7.35	6.68	12.63	10.24	6.70	7.25
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week of Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the number of divorce cases by average age of couples in columns (1)-(5), and the number of divorce cases by relative age difference (male-female) of couples in columns (4)-(6). All regressions use the 2SLS specification and use the thermal inversion measure as an instrument for the air quality index. Weather variables (temperature, precipitation, relative humidity, wind speed, sunshine duration, and air pressure), calendar week characteristics, county-by-year fixed effects, month fixed effects and week-of-month fixed effects are controlled in all columns.

Table A1: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline	Alternative Control Variables			Alternative S.E. Clustering		Alternative Thermal Inversion and Air Pollution Measures			
Dependent Variable	Divorce									
Air Quality Index	0.2087***	0.1750***	0.1324***	0.4179***	0.2087***	0.2087**	0.2358***	0.2643***		
	(0.0500)	(0.0577)	(0.0439)	(0.0943)	(0.0545)	(0.0919)	(0.0593)	(0.0668)		
$PM_{2.5}$									0.3310***	
									(0.0815)	
PM_{10}										0.1420***
										(0.0332)
Observations	2,704	2,704	2,704	2,704	2,704	2,704	2,704	2,704	2,704	2,704
1st-stage KP F-stat	162.0	120.0	222.2	77.6	616.3	14.6	150.2	115.8	102.7	269.2
Temperature Control	Parametric	Non-Parametric	Parametric	Parametric	Parametric	Parametric	Parametric	Parametric	Parametric	Parametric
Pollution Measure	AQI	AQI	AQI	AQI	AQI	AQI	AQI	AQI	$PM_{2.5}$	PM_{10}
Inversion Measure	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline	Alternative I	Alternative II	Baseline	Baseline
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	No	No	Yes	No	No	No	No	No	No	No
Week of Month FE	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Week of Year FE	No	No	No	Yes	No	No	No	No	No	No
Cluster	No	No	No	No	County	Week	No	No	No	No

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the number of divorce cases in all columns. Calendar week characteristics and county-by-year fixed effects are controlled in all columns. Weather variables (temperature, precipitation, relative humidity, wind speed, sunshine duration, and air pressure), month fixed effects and week-of-month fixed effects are controlled in all columns except for columns (2)-(4). The weather variables are replaced by the number of days within each quantile (5 quantiles in total, based on county-day level distribution in 2016-2019) of the county-week for each weather variable in column (2). The month fixed effects are replaced by year-by-month fixed effects in column (3). The week-of-month fixed effects are replaced by week-of-year fixed effects in column (4). Robust standard errors are used in all columns except for columns (5)-(6). In column (5), standard errors are clustered at county level. In column (6), standard errors are clustered at week level. All regressions use the 2SLS specification, and columns (1)-(6) use the baseline thermal inversion measure (the total number of thermal inversion events in the county-week, with thermal inversion events defined as the temperature of second layer being higher than that of first layer) as an instrument for the baseline pollution measure (air quality index). In column (7), the total number of days in the week having thermal inversion events, with thermal inversion events defined as the temperature of second layer being higher than that of first layer, is used as an instrument. In column (8), the total number of thermal inversion events in the county-week, with thermal inversion events defined as the temperature of third layer being higher than that of first layer, is used as an instrument. In column (9), $PM_{2.5}$ is used as air pollution measure. In column (10), PM_{10} is used as air pollution measure.

Table A2: Non-Linearity of the Effects of Thermal Inversion on Divorce

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Divorce	Divorce by Overall Education			Divorce by Relative Education		
Dependent Variable		High	Middle	Low	Equal	Male High	Male Low
# of Days with 1 Thermal Inversion Event	0.4081***	0.1107*	0.2027*	0.0947	0.3915***	0.0013	0.0153
	(0.1574)	(0.0611)	(0.1127)	(0.1025)	(0.1275)	(0.0529)	(0.0471)
# of Days with 2 Thermal Inversion Events	0.4489***	0.1234**	0.3057***	0.0198	0.4650***	-0.0192	0.0031
	(0.1555)	(0.0585)	(0.1141)	(0.0993)	(0.1230)	(0.0516)	(0.0480)
# of Days with 3~4 Thermal Inversion Events	1.1120***	0.3490**	0.8155***	-0.0524	0.7363**	0.2325*	0.1432
	(0.4044)	(0.1568)	(0.2705)	(0.2526)	(0.3250)	(0.1214)	(0.1092)
Observations	2,704	2,704	2,704	2,704	2,704	2,704	2,704
Mean of Dependent Variable	43.50	7.72	22.30	13.48	29.33	7.88	6.29
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week of Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the number of divorce cases in column (1), the number of divorce cases by average education of couples in columns (2)-(4), and the number of divorce cases by relative education between couples in columns (5)-(7). Weather variables (temperature, precipitation, relative humidity, wind speed, sunshine duration, and air pressure), calendar week characteristics, county-by-year fixed effects, month fixed effects and week-of-month fixed effects are controlled in all columns.