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# Impact of airborne pollen on stock market volatility☆

Ville Kaukonen [a], Mika Vaihekoski [a,*], Annika Saarto [b]

[a] University of Turku, School of Economics, Department of Accounting and Finance, 20014 Turun yliopisto, Finland
[b] University of Turku, Biodiversity Unit, 20014 Turun yliopisto, Finland

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ABSTRACT

Environmental factors have been shown to influence investor behavior through mood and cognitive channels, yet existing evidence based on weather-related proxies remains mixed. Unlike much of the previous environmental-finance literature, which primarily examines stock returns and weather-induced mood effects, this study focuses on whether airborne pollen exposure, a biologically grounded physiological stressor, influences stock market volatility itself.

Using daily Finnish pollen observations and stock market data from 1991–2024, we estimate an EGARCH-X model that incorporates pollen exposure together with weather variables, calendar effects, and market controls. The results indicate that elevated pollen exposure is associated with significantly lower conditional stock market volatility. The estimated relationship remains robust across alternative pollen measures, volatility specifications, distributional assumptions, and control sets.

To examine potential channels underlying the documented relationship, supplementary analyses incorporate aggregate trading activity, liquidity conditions, and market-segment heterogeneity. The findings suggest that the documented pollen effect is not mechanically explained by broad liquidity conditions and remains robust after accounting for trading activity. Moreover, the interaction results indicate that the volatility-reducing effect of elevated pollen exposure weakens as trading activity increases.

Overall, the findings are consistent with the interpretation that allergy-related physiological and cognitive burden may affect market participation and investor behavior. The study contributes to the literature by introducing a biologically grounded channel through which environmental conditions may influence financial market risk.

## 1. Introduction

Financial markets are influenced not only by economic fundamentals and information flows but also by behavioral and environmental factors that influence investor decision-making. A growing literature in behavioral finance suggests that psychological states, limited attention, and physiological conditions can influence financial behavior and market outcomes. In particular, theories of limited attention and cognitive scarcity emphasize that cognitive resources are finite and that external stressors may impair information processing and decision quality (Kahneman, 1973; Mani et al., 2013). Environmental variables such as weather

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* Corresponding author.
*E-mail addresses:* ville.kaukonen@utu.fi (V. Kaukonen), mika.vaihekoski@utu.fi (M. Vaihekoski), annika.saarto@utu.fi (A. Saarto).

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conditions, seasonal patterns, and mood-related factors have therefore attracted increasing attention as potential determinants of asset prices and trading behavior.

Prior research documents associations between environmental conditions and financial markets through several behavioral channels. Seasonal affective disorder (SAD), driven by changes in daylight exposure, has been linked to depression and reduced risk appetite, potentially generating seasonal patterns in stock returns (Kamstra et al., 2003). Similarly, increased sunshine has been associated with higher stock returns (Hirshleifer and Shumway, 2003), while darker periods linked to heightened SAD symptoms may increase risk premia (Garrett et al., 2005). However, empirical evidence on weather-related effects remains mixed. For example, Kaustia and Rantapuska (2016) find little robust evidence that local weather conditions exert economically meaningful effects on stock returns or trading behavior in Finland, suggesting that indirect mood-based weather proxies may have limited explanatory power in observed market outcomes.

Among environmental influences, airborne pollen represents a potentially important but relatively understudied factor. Unlike many weather-related variables that primarily operate indirectly through mood or sentiment, pollen exposure constitutes a biologically grounded physiological stressor that affects individuals through allergic reactions and related symptoms. Allergy-related responses have been associated with fatigue, impaired concentration, reduced cognitive performance, sleep disturbances, and diminished well-being (Schramm et al., 2021). These effects can influence investor attention, information processing, and market participation.

Existing evidence further suggests that pollen exposure may influence financial markets through behavioral channels. Pantzalis and Ucar (2017, 2018) report that allergy-induced symptoms reduce trading activity, weaken investors' demand for firm-specific information, and affect stock returns. Related studies also document that health shocks and environmental stressors, such as influenza outbreaks or air pollution, can impair cognitive functioning and influence financial outcomes (McTier et al., 2013; Kiihamäki et al., 2021). Nevertheless, relatively little attention has been devoted to whether airborne pollen exposure affects stock market volatility itself.

Understanding volatility effects may be particularly important because volatility reflects market uncertainty and risk rather than merely directional price movements. Whereas return effects describe changes in asset prices, volatility captures fluctuations in market conditions that may arise from changes in investor participation, information processing, and trading behavior. Consequently, if pollen exposure affects investor attention or market activity, its impact may be reflected in market volatility even when directional return effects remain weak.

The theoretical effect of pollen on volatility is ambiguous. On the one hand, negative affect and heightened risk perceptions may increase uncertainty and required risk premia (Symeonidis et al., 2010). On the other hand, reduced attention and lower market participation may dampen trading activity and thereby decrease realized and conditional volatility. Empirical findings from related settings reflect this ambiguity. Whereas Symeonidis et al. (2010) and Kiihamäki et al. (2021) report that environmental stressors may increase volatility, Chang et al. (2008) find that adverse weather conditions can reduce both trading activity and volatility.

This study contributes to the literature in three important respects. First, whereas much of the previous environmental-finance literature relies on weather variables as indirect proxies for mood (Hirshleifer and Shumway, 2003; Kamstra et al., 2003), airborne pollen represents a physiologically grounded environmental stressor that may influence cognitive functioning and investor behavior. Second, the present study focuses on conditional stock market volatility rather than only stock returns or trading volume, thereby examining whether environmental stress affects market uncertainty itself. Third, the empirical setting combines long-span daily pollen observations with an EGARCH-X framework, allowing the analysis to assess whether high-frequency variation in pollen exposure is associated with time-varying stock market volatility.

Using Finnish daily data covering the period from 1991 to 2024, we estimate EGARCH-X models that incorporate pollen exposure together with weather variables, calendar effects, and market controls. The empirical results indicate a robust inverse relationship between airborne pollen exposure and conditional stock market volatility. Elevated pollen levels are associated with significantly lower conditional variance across a broad range of alternative specifications, pollen measures, and distributional assumptions.

To further examine potential transmission channels, supplementary analyses investigate the roles of trading activity, market liquidity, and market-segment heterogeneity. The evidence suggests that the documented pollen effect is not mechanically explained by aggregate liquidity conditions and remains robust after accounting for trading activity. In addition, interaction results indicate that the volatility-reducing effect associated with elevated pollen exposure weakens as trading activity increases, suggesting that market participation may represent one potential transmission mechanism.

The identification strategy does not rely on broad comparisons across seasons but instead exploits day-to-day variation in pollen exposure while accounting for weather conditions, calendar effects, and other controls. Although the findings do not establish a definitive causal mechanism, they are consistent with the interpretation that allergy-related physiological burden affects investor behavior and market dynamics.

The remainder of the article proceeds as follows. Section 2 reviews the related literature and develops the theoretical motivation. Section 3 describes the data and empirical methodology. Section 4 presents the empirical results and robustness analyses. Section 5 concludes.

## 2. Theoretical background

Environmental conditions can influence financial markets through their effects on investor mood, cognition, and decision-making (Hirshleifer et al., 2020; Goodell et al., 2023). A substantial literature in behavioral finance documents that seemingly unrelated environmental factors affect risk-taking, trading behavior, and asset prices. One of the most extensively studied mechanisms is seasonal affective disorder (SAD), a mood disturbance associated with reduced daylight exposure. Prior research shows that seasonal variation in daylight is associated with predictable fluctuations in risk aversion and stock returns (Kamstra et al., 2014). Related evidence suggests that seasonal mood variation can influence investor behavior and financial-market outcomes more broadly (Keloharju et al., 2016). Similarly, sunshine has been linked to higher stock returns, suggesting that favorable environmental conditions improve investor sentiment and willingness to bear risk (Hirshleifer and Shumway, 2003).

The link between mood and financial decision-making is well established. Experimental evidence indicates that pleasant weather and sunlight increase risk-taking and trading activity (Bassi et al., 2013), whereas individuals affected by SAD exhibit lower risk tolerance during darker periods (Kramer and Weber, 2012). Beyond risk preferences, mood also affects attention and information processing. Positive affect broadens cognitive scope and facilitates information acquisition, whereas negative affect narrows attention and promotes more conservative decision-making (Fredrickson and Branigan, 2005). In financial settings, these mechanisms influence how investors process information, react to news, and participate in markets (Barberis and Thaler, 2003; Mbanga et al., 2019; Lonkani et al., 2025; Naidoo et al., 2025). Recent evidence further suggests that affective states influence not only expected returns but also market volatility through their effects on participation, risk-taking, and information processing (Kaplanski et al., 2015; Kliger and Levy, 2003).

While this literature demonstrates that environmental conditions can affect financial markets through mood and sentiment channels, most studies rely on weather-related variables that operate indirectly through psychological mechanisms. Airborne pollen represents a fundamentally different type of environmental influence because it constitutes a physiologically grounded stressor that directly affects human health and cognitive functioning (Trikojat et al., 2015; Papapostolou et al., 2021).

Pollen grains released by trees, grasses, and other seed plants commonly trigger allergic rhinitis and related respiratory conditions (Marcotte, 2015). Between 10 and 30 percent of the global population suffers from pollen-related allergic diseases (Zhang et al., 2015), and approximately one-fifth of Finns are affected (Varjonen et al., 1992). Exposure is widespread because pollen remains airborne for extended periods, can travel considerable distances, and is frequently detected indoors, including office environments (Oh, 2022; Farrera et al., 2002).

A growing medical literature demonstrates that allergic reactions affect not only physical well-being but also cognition and mood. Allergic rhinitis is associated with fatigue, impaired concentration, reduced attention, slower reaction times, and diminished working-memory capacity (Trikojat et al., 2015; Marshall et al., 2000; Papapostolou et al., 2021). Psychological symptoms frequently accompany these effects, with studies documenting elevated anxiety, depressive symptoms, and deteriorating mood during periods of high pollen exposure (Hurwitz and Morgenstern, 1999; Oh et al., 2018; Guzman et al., 2007). Finnish cohort evidence further suggests that atopic diseases are associated with a higher risk of depression in early adulthood (Timonen et al., 2003). Biologically, these outcomes are linked to inflammatory processes that influence neural pathways involved in mood regulation and cognitive control (Postolache et al., 2007). Collectively, this evidence suggests that pollen exposure can reduce attention, cognitive efficiency, and motivation, all of which are important determinants of financial decision-making.

These cognitive and behavioral effects provide a natural link between pollen exposure and financial-market outcomes. Direct evidence is provided by Pantzalis and Ucar (2017), who show that elevated pollen concentrations are associated with lower stock returns and reduced trading activity in the United States. In a follow-up study, Pantzalis and Ucar (2018) demonstrate that allergy onset reduces investor participation and weakens reactions to earnings-related information. Together, these studies suggest that pollen-induced impairments in attention and decision-making can influence aggregate market outcomes through reduced participation and slower information processing.

Despite this growing evidence, existing research has focused primarily on stock returns, trading activity, investor distraction, and information acquisition. Much less attention has been devoted to whether biologically grounded environmental stressors influence stock market volatility itself. Consequently, it remains unclear whether pollen exposure affects not only investor decisions but also the dynamics of market risk and uncertainty. This study addresses that gap by examining the relationship between airborne pollen exposure and conditional stock market volatility.

Comparable mechanisms have been documented in studies of infectious disease and air pollution. McTier et al. (2013) show that influenza outbreaks reduce trading activity and volatility through absenteeism and lower information production, while studies of air quality report effects on investor sentiment, market participation, liquidity, and asset prices (He and Liu, 2018; Wu and Lu, 2020; An et al., 2018; Teng and He, 2020). Although the direction of volatility effects varies across settings, these findings collectively suggest that environmental stressors can influence financial markets through mood, attention, and participation channels.

Limited-attention and rational-inattention models provide a theoretical foundation for these mechanisms. When information processing is costly or cognitive resources are constrained, investors allocate attention selectively across assets and time (Sims, 2003; Peng and Xiong, 2006; Veldkamp, 2006). Environmental stressors that impair cognition may therefore reduce information acquisition, delay price discovery, and weaken reactions to new information. Because trading activity and information flow are closely linked to volatility in market-microstructure models (Karpoff, 1987; Jones et al., 1994), attention constraints that suppress participation can reduce conditional volatility. Consistent with this interpretation, DellaVigna and Pollet (2009) show that limited attention leads to weaker responses to public information, while Andrei and Hasler (2015) demonstrate that investor attention is closely related to return variance and risk premia. Within this framework, pollen exposure can be viewed as a temporary, largely exogenous constraint on aggregate investor attention.

Pollen exposure may also affect volatility through a sentiment channel. Prior research suggests that favorable environmental conditions can increase risk-taking, trading activity, and volatility through improved investor mood (Symeonidis et al., 2010). Conversely, adverse affect and allergy-related cognitive fatigue may reduce participation and information processing, lowering market activity and volatility. However, some studies argue that negative mood may also increase disagreement and speculative behavior, implying potentially higher volatility (Chang et al., 2008). The overall effect therefore remains an empirical question.

The mechanism considered in this study can therefore be summarized as follows. Elevated pollen exposure impairs cognition and attention through allergic inflammation, fatigue, and mood disturbances. Reduced attention lowers investors' willingness and ability to process information, leading to lower trading activity and weaker reactions to news. Reduced participation and information flow subsequently dampen order-flow variability and price adjustment dynamics, thereby lowering conditional market volatility. The magnitude of the effect may vary across investor groups if retail investors are more susceptible to mood and attention-related constraints than institutional investors.

More broadly, these behavioral and cognitive mechanisms relate to a growing literature examining how environmental conditions and health-related factors influence investor behavior and financial markets (Hong et al., 2019; Bolton and Kacperczyk, 2023). In this context, pollen exposure can be viewed as a biologically grounded, micro-level environmental shock that affects investor behavior through health, productivity, mood, and attention channels. This perspective also contributes to a broader literature emphasizing that financial-market volatility is shaped by multiple interacting sources of shocks and evolving patterns of investor behavior (Kyriazis et al., 2026; Dimitriadis et al., 2025b,a). Existing studies have focused predominantly on financial, macroeconomic, and institutional determinants of volatility, while largely overlooking biologically grounded environmental stressors that may influence investor attention and market participation. By examining airborne pollen exposure, the present study extends the volatility literature to a novel source of behavioral variation originating outside the financial system itself.

These theoretical considerations suggest that airborne pollen exposure may influence financial-market volatility through attention, sentiment, and participation channels. By impairing cognitive functioning and reducing investors' willingness or ability to process information, elevated pollen levels may dampen trading activity and information flow, thereby affecting conditional volatility. The empirical analysis that follows examines whether this theoretically motivated relationship is observable in aggregate stock-market data.

Based on the theoretical arguments outlined above, this study hypothesizes that elevated pollen exposure is associated with lower conditional stock market volatility.

## 3. Data and research methods

### 3.1. Data

We use the daily OMX Helsinki (OMXH) Total Return General Index as a proxy for the Finnish equity market. The OMXH is an all-share, value-weighted index that accounts for dividends and corporate actions. To capture broader European market dynamics, we include the German DAX Performance Total Return Index, reflecting Finland's strong financial and economic linkages with Germany. Both indices are obtained from LSEG Datastream. The dependent variable is the continuously compounded total return of the OMXH Index, while the DAX return is included as a regressor in the mean equation. The sample begins in 1991, reflecting availability of pollen data.

To proxy pollen-induced allergy exposure, we use daily airborne pollen counts reported as daily average pollen concentrations (grains per cubic meter of air) aggregated across all measured species.[1] For the empirical analysis, we have two pollen time series. The one with a longer history is from the City of Turku, available from January 3, 1991, onwards, and the second one is for Helsinki, available from February 17, 2015, onwards. The direct distance from Turku, Finland's former capital, to Helsinki, in the east, is approximately 93 miles. As the prevailing wind direction in Finland's southern coastal area is most often southwest (see https://en.ilmatieteenlaitos.fi/climate-elements), one can expect pollen levels in both cities to be highly correlated. This is indeed the case. For the overlapping pollen subsample from February 17, 2015, to September 27, 2024 (1337 daily observations), the correlation between pollen concentrations in Turku and Helsinki is 0.764 and statistically significant at the 1% level. As a result, we combine the Turku and Helsinki series into a single time series, yielding 7119 daily observations after removing missing values and non-trading days.

Using the pollen time series, we construct five pollen-based variables. The primary measure is the daily total pollen count (*TP*), defined as the sum of all species.[2] We also use its logarithmic transformation, $\log(1 + TP)$, to reduce skewness and stabilize variance (Postolache et al., 2005; Yli-Panula et al., 2009; Lake et al., 2017). To capture potential nonlinear exposure effects, we define a percentile-based categorical measure following Pantzalis and Ucar (2018), which groups *TP* into five exposure levels based on its empirical distribution.

In addition, we construct a threshold indicator, (*TP150*) equal to one when *TP* exceeds 150 grains/m$^3$, corresponding to clinically relevant exposure levels associated with heightened allergic symptoms (see Viander and Koivikko, 1978; Rantio-Lehtimäki et al., 1991, 1994; Kilpeläinen et al., 2002; Burbach et al., 2009). Finally, unexpected changes in pollen are measured using the innovation from an AR(1) model:

$$\epsilon_t = TP_t - \alpha_0 - \phi_1 TP_{t-1}, \tag{1}$$

[1] Pollen sampling is conducted using a Hirst-type volumetric sampler (Hirst, 1952) installed at rooftop level. For details on sampling methodology, see Mäkinen (1981).

[2] Although birch pollen typically dominates during spring, other species may contribute substantially in some years (see Kilpeläinen et al., 2002; Burbach et al., 2009).

where $TP_t$ denotes the total daily pollen count, $\alpha_0$ is the intercept, and $\phi_1$ is the autoregressive parameter.

For the monthly analysis, daily pollen counts are aggregated into five variables: (i) the monthly sum ($\sum TP_d$), (ii) the monthly average ($\overline{TP_d}$), (iii) a threshold indicator (*TH150*) equal to one if *TP* exceeds 150 on any day within the month, (iv) the number of exceedance days (#Days ≥ TH150), and (v) an indicator equal to one if the monthly mean exceeds 100 grains/m$^3$ ($\overline{TP_d} \geq 100$). The monthly sample covers January 1991 through September 2024 (344 observations).

Weather conditions partly determine pollen release and may also influence investor behavior. To account for these effects, we include daily total precipitation (mm) and average air temperature (in Kelvin) as control variables. Both series are obtained from the Finnish Meteorological Institute (FMI) and measured in Helsinki (Kaisaniemi district), providing a consistent proxy for local environmental conditions relevant to investors.

For robustness, we analyze subsamples corresponding to the Turku (1991–2014) and Helsinki (2015–2024) pollen series, using *TP150* as the variance regressor. In addition to total pollen, we consider allergenic pollen (*AP*), defined as the sum of five clinically relevant species known to induce seasonal allergic rhinitis: alder (*Alnus*), birch (*Betula*), grasses (*Poaceae*), hazel (*Corylus avellana*), and mugwort (*Artemisia vulgaris*). Observations are retained when all five species are recorded, resulting in 6873 valid observations.

### 3.2. Research method

To examine the effect of pollen-induced allergies on stock market volatility, we employ the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework (see, *e.g.*, Bollerslev, 1986; Taylor, 2008). Originally introduced as ARCH models by Engle (1982), this framework captures the characteristic clustering of high and low volatility in financial returns and allows incorporating exogenous variables—such as pollen counts and weather controls (precipitation and temperature)—to study their impact on market risk.

The conditional mean of Finnish stock returns is modeled as

$$r_{OMXH,t} = \alpha + \beta r_{DAX,t} + \epsilon_t, \tag{2}$$

where $r_{OMXH,t}$ and $r_{DAX,t}$ denote continuously compounded logarithmic returns of the OMX Helsinki and DAX Performance Total Return indices, respectively, and $\epsilon_t \mid \mathcal{F}_{t-1} \sim \mathcal{N}(0, \sigma_t^2)$, or alternatively $\epsilon_t \mid \mathcal{F}_{t-1} \sim \sigma_t z_t$, where $z_t \sim t_\nu$ is a standardized Student's $t$-distributed error term with $\nu > 2$ degrees of freedom. The coefficient $\beta$ measures the sensitivity of Finnish returns to movements in the broader European market.

For volatility dynamics, two models are compared: the standard GARCH, which often works even with shorter samples, and the more advanced Exponential GARCH, which typically requires longer samples. The general GARCH($p, q$) specification is

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{3}$$

where $\sigma_t^2$ is the conditional variance, $\omega$ the long-term variance level, $\alpha_i$ measures the impact of past shocks, and $\beta_j$ captures volatility persistence.

Long samples with a high number of observations also allow us to use the EGARCH model, which captures asymmetric and exogenous effects (Nelson, 1991). Both models can be extended to include exogenous variables, such as the ones used here. For example, in the case of EGARCH($p, q$)-X, the full model becomes:

$$\begin{aligned} \log(\sigma_t^2) = \omega &+ \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left| \frac{\epsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^{p} \gamma_k \frac{\epsilon_{t-k}}{\sigma_{t-k}} \\ &+ \lambda_1 \mathrm{Pollen}_t + \lambda_2 \mathrm{Precipitation}_t + \lambda_3 \mathrm{Temperature}_t, \end{aligned} \tag{4}$$

where $\log(\sigma_t^2)$ ensures positivity, $\gamma_k$ captures leverage effects ($\gamma_k < 0$ indicates that negative shocks increase volatility more than positive ones), and the coefficients ($\lambda_1, \lambda_2, \lambda_3$) measure the impact of environmental variables on volatility. In particular, $\lambda_1$ captures the effect of airborne pollen exposure, which is the primary variable of interest in this study.[3]

Parameter estimation proceeds by maximum likelihood using the Broyden–Fletcher– Goldfarb–Shanno (BFGS) algorithm with Marquardt steps (see Fletcher, 2000). Robust Huber–White standard errors (Huber, 1967; White, 1980) are employed to account for potential misspecification. The model is estimated by maximum likelihood assuming either Gaussian or Student's $t$-distributed errors (Francq and Thieu, 2019). Backcasting with a smoothing parameter of 0.7 is used to initialize presample variances.

To quantify the economic importance of the pollen effect, we compute

$$\text{Economic Significance} = \left| \frac{\hat{\lambda}_1 \cdot \mathrm{SD}(\mathrm{Pollen}_t)}{\overline{\log(\hat{\sigma}_t^2)}} \right|, \tag{5}$$

where $\hat{\lambda}_1$ is the estimated coefficient on pollen, SD(Pollen$_t$) its standard deviation, and $\overline{\log(\hat{\sigma}_t^2)}$ the sample average of fitted log variance. The numerator measures the effect on log volatility from a one-standard-deviation increase in pollen exposure, while the denominator normalizes this effect relative to the average volatility level.

This framework provides a robust basis for examining how environmental shocks, such as pollen exposure, influence investor behavior and financial market volatility. The following section presents the empirical results derived from these specifications.

[3] We slightly deviate from Nelson (1991), who centers the absolute standardized residual term; our parameterization is equivalent except for the intercept adjustment $\alpha_i \sqrt{2/\pi}$ under normality.

**Table 1**
Descriptive statistics for daily logarithmic total returns and regressors. *OMXH Return (%)* and *DAX Return (%)* denote the daily logarithmic total returns of the OMX Helsinki Index (Finland) and the DAX Performance Index (Germany), expressed in percent. Regressors include pollen and weather variables. The primary pollen variables are constructed from daily concentrations of *Total Pollen (TP)*, defined as the sum of pollen counts across all measured species. The series combines 5782 observations from Turku (1991–2014) and 1337 from Helsinki (2015–2024). Missing values and non-trading days were removed, leaving 7119 daily observations. *Log TP* is the natural logarithm of *TP* plus one. *Surprise TP* is the AR(1) innovation. *TP Percentile* classifies *TP* into absent, low (<50th percentile), moderate (50th–75th percentile), high (75th–99th percentile), and very high (>99th percentile), coded as 0, 0.25, 0.625, 0.875, and 0.995, respectively. The threshold indicator *TP150* equals one if $TP \geq 150$ grains/m$^3$. *Precipitation* (mm, daily total) and *Temperature* (K, daily average) are also included. Autocorrelation is reported at lags 1–3 ($\rho_1$, $\rho_2$, $\rho_3$); ADF tests for unit roots. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

| Variable | Mean | Minimum | Maximum | Std. Dev. | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| OMXH return (%) | 0.046 | −17.172 | 14.563 | 1.641 | −0.215 | 9.893 |
| DAX return (%) | 0.026 | −9.871 | 10.797 | 1.409 | −0.162 | 8.111 |
| Total Pollen (TP) | 145.115 | 0.000 | 17,898.000 | 647.057 | 13.846 | 274.293 |
| Log TP | 2.351 | 0.000 | 9.793 | 2.378 | 0.450 | 1.953 |
| Surprise TP | −0.007 | −8251.237 | 13,641.671 | 477.357 | 10.282 | 256.272 |
| TP percentile | 0.417 | 0.000 | 0.995 | 0.381 | −0.059 | 1.233 |
| TP150 | 0.156 | 0.000 | 1.000 | 0.363 | 1.895 | 4.593 |
| Precipitation | 1.771 | 0.000 | 52.000 | 4.146 | 4.372 | 30.757 |
| Temperature | 280.833 | 249.950 | 299.550 | 8.565 | −0.331 | 2.504 |

| Variable | Autocorrelation | | | ADF |
|---|---|---|---|---|
| | $\rho_1$ | $\rho_2$ | $\rho_3$ | $t$-statistic |
| OMXH return (%) | 0.045*** | −0.016*** | −0.005*** | −80.658*** |
| DAX return (%) | 0.001 | −0.031** | −0.029*** | −84.246*** |
| Total Pollen (TP) | 0.675*** | 0.381*** | 0.282*** | −30.365*** |
| Log TP | 0.872*** | 0.838*** | 0.819*** | −8.797*** |
| Surprise TP | 0.092*** | −0.167*** | −0.019*** | −67.941*** |
| TP percentile | 0.782*** | 0.751*** | 0.748*** | −7.554*** |
| TP150 | 0.658*** | 0.597*** | 0.526*** | −12.694*** |
| Precipitation | 0.164*** | 0.086*** | 0.070*** | −41.586*** |
| Temperature | 0.952*** | 0.913*** | 0.886*** | −7.265*** |

## 4. Empirical results

### 4.1. Descriptive statistics and introductory analysis

Table 1 reports descriptive statistics for the daily logarithmic total returns and the main explanatory variables. The final sample consists of 7119 daily observations from January 1991 to September 2024 after aligning market trading days and removing missing values.

The return series exhibits the standard properties of daily equity data. OMX Helsinki (OMXH) and DAX Performance (DAX) Index returns are approximately symmetric, display excess kurtosis, and show only weak short-run autocorrelation. Their Augmented Dickey–Fuller (ADF) test statistics strongly reject the null of a unit root, confirming stationarity. By contrast, the pollen variables are substantially more skewed, persistent, and fat-tailed, reflecting the strongly seasonal and episodic nature of airborne pollen exposure. The raw pollen series has a mean of 145.12 grains per cubic meter and a standard deviation of 647.06, while the log transformation yields a considerably more regular distribution. The innovation-based surprise measure remains volatile, as expected, and the threshold- and percentile-based measures provide more balanced proxies for elevated pollen intensity.

Fig. 1 illustrates the pronounced seasonal structure of pollen exposure in Finland. Fig. 1a shows that pollen intensity increases sharply during spring, peaks in late spring and early summer, and gradually declines toward autumn. Fig. 1b demonstrates that non-zero pollen observations are concentrated within a well-defined seasonal window, whereas pollen exposure remains negligible during winter months. Together, the panels indicate that pollen exposure is both highly seasonal and persistent within the active pollen season.

The weather variables display patterns consistent with Northern European climatic conditions. Daily precipitation is right-skewed because of occasional heavy rainfall episodes, whereas temperature is highly persistent due to seasonal smoothness. Overall, the descriptive evidence indicates that stock returns behave like conventional financial time series, while pollen and weather variables represent persistent environmental processes with pronounced seasonality. These features motivate the use of log transformations, innovation-based pollen measures, and conditional volatility models in the subsequent analysis.

Table 2 presents the Pearson correlations among returns, pollen variables, and weather controls. As expected, OMXH and DAX returns are strongly positively correlated, reflecting close integration between the Finnish and German equity markets. By contrast, the contemporaneous correlations between stock returns and the pollen variables are weak in magnitude, although some are statistically significant. This pattern suggests that pollen exposure is unlikely to operate through a direct return channel. Rather, if

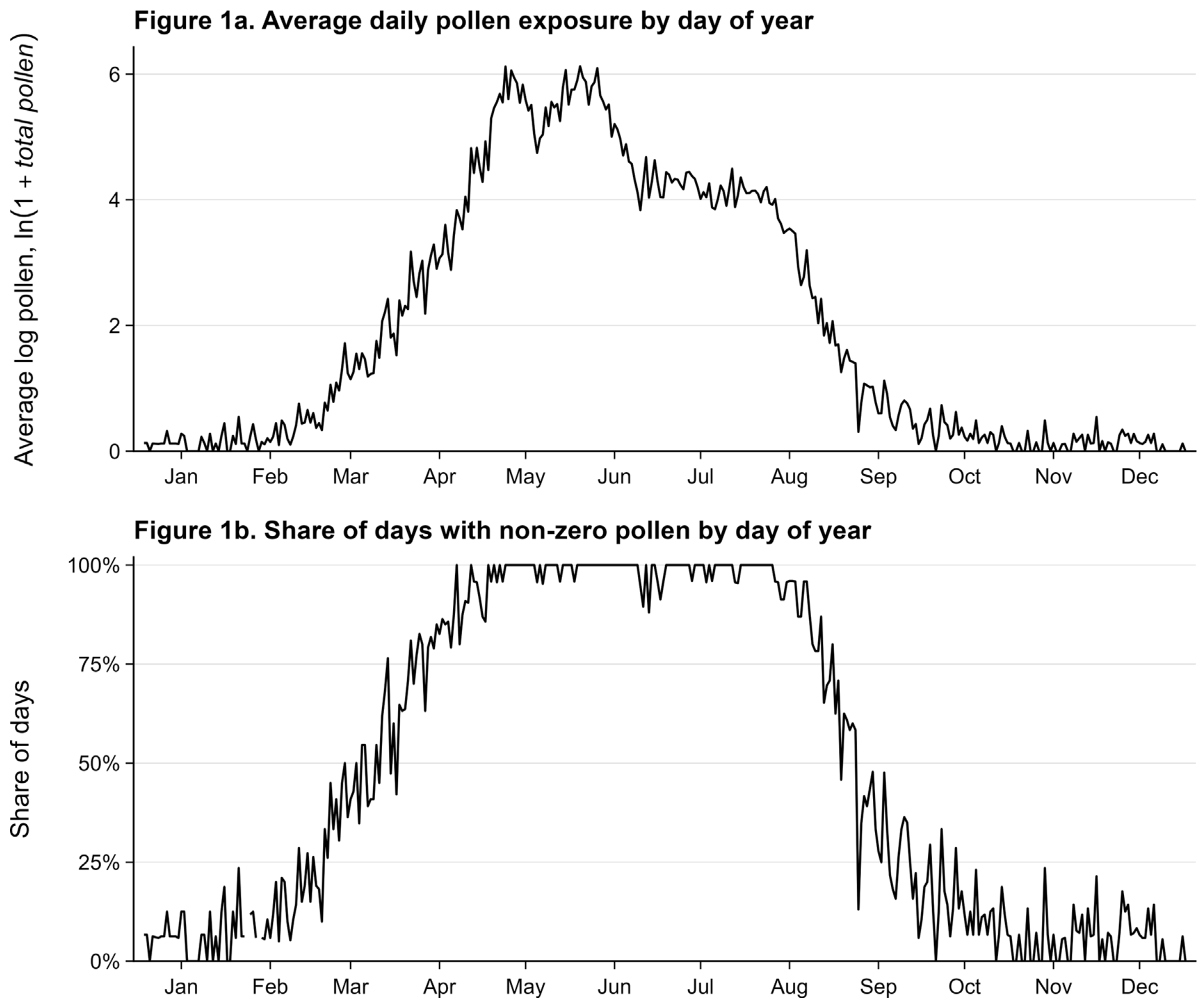


**Fig. 1.** Seasonal pattern of pollen exposure in Finland. Fig. 1a shows the average daily pollen level by day of the year, expressed as $\ln(1 + Pollen)$. Fig. 1b reports the corresponding share of days with non-zero pollen counts. The figure illustrates a pronounced and recurring seasonal pattern, with both pollen intensity and exposure frequency peaking in late spring and summer and remaining close to zero during winter.

**Table 2**
Correlation analysis. Pearson correlation coefficients for the study variables (defined in Table 1) are based on 7119 daily observations from January 3, 1991, to September 27, 2024, excluding non-trading days. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | OMXH return | DAX return | TP | Log TP | Surprise TP | TP percentile | TP150 | Precipitation |
|---|---|---|---|---|---|---|---|---|
| DAX return | 0.657*** | | | | | | | |
| TP | −0.005 | 0.001 | | | | | | |
| Log TP | −0.032*** | −0.012 | 0.438*** | | | | | |
| Surprise TP | −0.002 | 0.004 | 0.738*** | 0.238*** | | | | |
| TP percentile | −0.031*** | −0.016 | 0.286*** | 0.947*** | 0.142*** | | | |
| TP150 | −0.022* | −0.009 | 0.441*** | 0.682*** | 0.234*** | 0.525*** | | |
| Precipitation | 0.003 | −0.009 | −0.049*** | −0.064*** | −0.036*** | −0.040*** | −0.080*** | |
| Temperature | −0.036*** | −0.030** | 0.148*** | 0.602*** | 0.070*** | 0.612*** | 0.291*** | 0.051*** |

pollen matters for financial markets, its effects are more likely to emerge through changes in investor behavior, market participation, or risk-taking.

The pollen variables are naturally correlated with one another, especially the log-transformed, surprise, percentile-based, and threshold-based measures. Temperature is positively associated with pollen intensity, whereas precipitation is negatively related to pollen, consistent with the biological and meteorological determinants of pollen release and dispersion. For the overlapping

**Table 3**

Baseline GARCH and EGARCH results. Estimation results for GARCH and EGARCH models applied to daily logarithmic total returns of the OMX Helsinki Index. Panel A reports the mean equation, including the daily log returns of the DAX Performance Index as a regressor. Panel B reports the variance equation without covariates. Errors are assumed to follow either a normal (Gaussian) or Student's $t$ distribution, and standard errors are computed using the Huber–White robust covariance estimator. $t$-statistics are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels. Diagnostic measures include the log-likelihood and Akaike, Schwarz, and Hannan-Quinn information criteria.

| Coefficient | GARCH(1,1) | | EGARCH(1,1) | |
|---|---|---|---|---|
| | Normal | Student's $t$ | Normal | Student's $t$ |
| Panel A: Mean equation | | | | |
| $\alpha$ ($\times 10^3$) | 0.260** | 0.249*** | 0.210** | 0.246*** |
| | (2.559) | (2.848) | (2.100) | (2.866) |
| $\beta$ | 0.742*** | 0.751*** | 0.741*** | 0.751*** |
| | (57.986) | (75.542) | (63.837) | (86.591) |
| Panel B: Variance equation | | | | |
| $\omega$ | 0.000 | 0.000*** | −0.086*** | −0.111*** |
| | (1.540) | (2.981) | (−2.602) | (−5.204) |
| $\alpha_1$ | 0.028*** | 0.042*** | 0.086*** | 0.110*** |
| | (3.836) | (5.359) | (3.455) | (7.014) |
| $\gamma_1$ | | | −0.010 | −0.001 |
| | | | (−1.515) | (−0.135) |
| $\beta_1$ | 0.971*** | 0.956*** | 0.998*** | 0.997*** |
| | (123.451) | (117.780) | (552.146) | (773.226) |
| Log-likelihood | 22,893.119 | 23,218.169 | 22,913.360 | 23,245.333 |
| Akaike | −6.430 | −6.521 | −6.436 | −6.529 |
| Schwarz | −6.425 | −6.515 | −6.430 | −6.522 |
| Hannan-Quinn | −6.428 | −6.519 | −6.434 | −6.526 |

period from February 2015 to September 2024, total pollen concentrations measured in Turku and Helsinki are strongly correlated, supporting the use of the merged pollen series as a representative indicator of regional pollen conditions in Southern Finland. Additional descriptive evidence on the long-run variation and stability of pollen exposure is reported in the Internet Appendix.

Overall, the descriptive statistics and correlation analysis suggest that pollen exposure constitutes a plausible exogenous environmental factor with the potential to influence financial-market behavior, even though its simple contemporaneous association with returns is limited. This motivates a more formal examination of whether pollen exposure helps explain variation in stock market volatility.

### *4.2. Main analysis of pollen and risk*

Table 3 first reports the benchmark GARCH(1,1) and EGARCH(1,1) estimates for daily OMX Helsinki returns. Across all specifications, the coefficient on contemporaneous DAX returns is positive and highly significant, confirming the strong comovement between Finnish and German equity markets. The conditional variance dynamics are standard and highly persistent, as is typical for daily stock returns. In terms of overall fit, the EGARCH(1,1) model with Student's $t$ errors outperforms the alternative baseline specifications and is therefore used as the main framework for the extended analysis. Additional robustness evidence based on alternative volatility specifications is reported in Internet Appendix Table A2.

The main results are presented in Table 4, where the preferred EGARCH(1,1)-X specification includes alternative pollen measures in the variance equation. Across all five definitions of pollen exposure, the coefficient on the pollen variable is negative. More importantly, the estimated coefficients remain statistically significant across specifications, indicating a robust inverse association between airborne pollen intensity and conditional stock market volatility. This is the central empirical result of the paper.

The result is not driven by one particular operationalization of pollen. The negative association appears for the raw total pollen series, its logarithmic transformation, the surprise component extracted from the AR(1) model, the percentile-based exposure measure, and the threshold indicator for high-pollen days. Among these, the threshold-based measures produce the strongest and most stable estimates. In particular, the coefficient on *TP150* is statistically the strongest and most stable among the alternative pollen specifications, suggesting that the volatility effect is strongest during periods of unusually elevated pollen exposure rather than from marginal fluctuations within the normal range.

The estimated relationship does not appear to be driven solely by broad seasonal patterns or omitted market dynamics. Internet Appendix Table A1 reports a sequence of progressively enriched specifications that incorporate weekday effects, a summer indicator, lagged international spillovers, additional domestic market controls, and winsorized pollen measures. Across all specifications, the estimated pollen coefficient remains negative and statistically significant, confirming that the findings are robust to alternative control structures and are not driven by extreme observations or broad calendar-based seasonal patterns.

The economic magnitude of the estimates is modest but non-negligible. For example, when pollen counts exceed 150 grains $m^{-3}$, model-implied daily conditional log variance declines by roughly −0.0169. To facilitate interpretation, we evaluate the economic

**Table 4**

EGARCH-X results with alternative covariates (daily data without controls). Estimation results for EGARCH-X models applied to daily logarithmic total returns of the OMX Helsinki Index. Panel A reports the mean equation, including daily log returns of the DAX Performance Index as a regressor. Panel B reports the variance equation with five alternative variance regressors. Variables are defined in Table 1, and $\lambda_1$ denotes their coefficient estimates. Errors are assumed to follow a Student's $t$ distribution, and standard errors are computed using the Huber–White robust covariance estimator. Diagnostic measures include the log-likelihood and the Akaike, Schwarz, and Hannan-Quinn information criteria. Economic significance is calculated as the product of the estimated pollen coefficient and the standard deviation of the pollen time series, divided by the average log conditional variance from the EGARCH-X model. $t$-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| Coefficient | TP | Log TP | Surprise TP | TP percentile | TP150 |
|---|---|---|---|---|---|
| Panel A: Mean equation | | | | | |
| $\alpha$ ($\times 10^3$) | 0.241*** | 0.241*** | 0.240*** | 0.242*** | 0.239*** |
| | (2.791) | (2.808) | (2.665) | (15.328) | (2.801) |
| $\beta$ | 0.751*** | 0.751*** | 0.751*** | 0.751*** | 0.751*** |
| | (73.791) | (77.427) | (142.835) | (143.915) | (85.253) |
| Panel B: Variance equation | | | | | |
| $\omega$ | −0.111*** | −0.112*** | −0.112*** | −0.112*** | −0.110*** |
| | (−5.296) | (−5.322) | (−5.329) | (−5.288) | (−5.423) |
| $\alpha_1$ | 0.109*** | 0.109*** | 0.109*** | 0.109*** | 0.107*** |
| | (7.020) | (7.123) | (7.010) | (7.104) | (7.121) |
| $\gamma_1$ | −0.002 | −0.003 | −0.002 | −0.003 | −0.004 |
| | (−0.382) | (−0.603) | (−0.347) | (−0.551) | (−0.814) |
| $\beta_1$ | 0.997*** | 0.996*** | 0.997*** | 0.996*** | 0.997*** |
| | (781.648) | (746.282) | (783.430) | (737.012) | (799.972) |
| $\lambda_1^{\text{Pollen}}$ ($\times 10^3$) | −0.009** | −1.475*** | −0.025** | −8.290** | −16.851*** |
| | (−2.333) | (−2.769) | (−2.265) | (−2.436) | (−3.588) |
| Log-likelihood | 23,248.150 | 23,249.372 | 23,247.830 | 23,248.435 | 23,251.722 |
| Akaike | −6.529 | −6.529 | −6.529 | −6.529 | −6.530 |
| Schwarz | −6.521 | −6.522 | −6.521 | −6.521 | −6.522 |
| Hannan-Quinn | −6.526 | −6.527 | −6.526 | −6.526 | −6.527 |
| Economic significance (%) | 0.062 | 0.038 | 0.126 | 0.034 | 0.066 |

magnitude of the estimated effect relative to the average level of conditional volatility. The estimated coefficient implies that high-pollen days are associated with approximately 1.67% lower conditional variance and 0.84% lower conditional volatility. The effect is therefore not large in absolute terms, but it is systematic, statistically robust, and potentially meaningful in the context of daily market volatility, where even modest changes may accumulate over time.

The estimated effect is also broadly consistent with behavioral explanations commonly discussed in the finance literature. One possible mechanism is that elevated pollen exposure increases allergy-related discomfort, fatigue, and cognitive strain, thereby reducing investor attention, trading intensity, or willingness to take risks. If a subset of investors becomes less active or less responsive during periods of unusually high pollen exposure, short-run price fluctuations may become more muted, which could be reflected in lower conditional volatility. In this sense, the findings appear broadly consistent with an attention- and participation-based interpretation rather than a direct pricing effect operating through the conditional mean equation.

This interpretation is broadly in line with earlier work suggesting that environmental conditions can influence financial outcomes through investor behavior rather than purely through fundamental channels (Pantzalis and Ucar, 2017). It also complements recent research on dynamic spillovers and volatility transmission, which emphasizes that market risk may be driven by a range of interacting forces beyond purely macroeconomic or financial linkages (Dimitriadis et al., 2025b). External non-financial conditions may therefore influence market dynamics when they systematically affect human behavior and decision-making.

### *4.3. Additional analysis and robustness checks*

Table 5 extends the daily EGARCH analysis by including precipitation and temperature as additional controls in the variance equation. The main result remains unchanged. Across all pollen definitions, the coefficient on pollen exposure stays negative and statistically significant, and its magnitude remains close to that of the baseline specification. By contrast, the weather controls themselves are statistically insignificant throughout. This indicates that the negative pollen–volatility relationship is not simply a proxy for short-term temperature or rainfall conditions.

This result is important for interpretation. Since pollen is closely related to seasonal weather patterns, one might worry that the baseline findings merely reflect broader meteorological conditions rather than pollen exposure per se. The estimates in Table 5 do not support that concern. Instead, they suggest that once pollen exposure is explicitly included, short-term weather fluctuations do not exert an independent effect on volatility. Hence, the pollen coefficient appears to capture something more specific than general seasonal weather variation.

**Table 5**
EGARCH-X results with alternative covariates (daily data with controls). Estimation results for EGARCH-X models applied to daily logarithmic total returns of the OMX Helsinki Index. Panel A reports the mean equation, including daily log returns of the DAX Performance Index as a regressor. Panel B reports the variance equation, incorporating five alternative variance regressors. Variables are defined in Table 1. $\lambda_1$ denotes the coefficient estimate for the pollen variable, while $\lambda_2$ and $\lambda_3$ correspond to the control variables, *Precipitation* and *Temperature*. Errors are assumed to follow a Student's $t$ distribution, and standard errors are computed using the Huber–White robust covariance estimator. Diagnostic measures include the log-likelihood, Akaike, Schwarz, and Hannan-Quinn information criteria. Economic significance is calculated as the product of the estimated pollen coefficient and the standard deviation of the pollen series, divided by the average log conditional variance from the EGARCH-X model. $t$-statistics are in parentheses, and ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| Coefficient | TP | Log TP | Surprise TP | TP Percentile | TP150 |
|---|---|---|---|---|---|
| Panel A: Mean equation | | | | | |
| $\alpha$ ($\times 10^3$) | 0.240*** | 0.242** | 0.239** | 0.243*** | 0.240*** |
| | (2.768) | (2.563) | (2.321) | (2.614) | (2.808) |
| $\beta$ | 0.751*** | 0.751*** | 0.751*** | 0.751*** | 0.751*** |
| | (72.050) | (117.962) | (50.937) | (129.596) | (86.090) |
| Panel B: Variance equation | | | | | |
| $\omega$ | −0.071* | −0.142** | −0.068* | −0.130** | −0.110*** |
| | (−1.748) | (−2.257) | (−1.672) | (−2.186) | (−5.352) |
| $\alpha_1$ | 0.110*** | 0.109*** | 0.110*** | 0.110*** | 0.108*** |
| | (7.053) | (7.169) | (7.004) | (7.133) | (7.180) |
| $\gamma_1$ | −0.003 | −0.004 | −0.003 | −0.003 | −0.005 |
| | (−0.513) | (−0.592) | (−0.491) | (−0.568) | (−0.831) |
| $\beta_1$ | 0.996*** | 0.996*** | 0.996*** | 0.996*** | 0.997*** |
| | (735.782) | (742.916) | (733.034) | (731.063) | (796.051) |
| $\lambda_1^{\text{Pollen}}$ ($\times 10^3$) | −0.008** | −1.844** | −0.022* | −9.759* | −18.099*** |
| | (−1.977) | (−2.229) | (−1.910) | (−1.877) | (−3.721) |
| $\lambda_2^{\text{Precip.}}$ ($\times 10^3$) | −0.417 | −0.861 | −0.372 | −0.630 | −1.056 |
| | (−0.458) | (−0.753) | (−0.354) | (−0.614) | (−1.072) |
| $\lambda_3^{\text{Temp.}}$ ($\times 10^3$) | −0.152 | 0.116 | −0.169 | 0.068 | 0.007 |
| | (−1.018) | (0.515) | (−1.138) | (0.321) | (0.289) |
| Log-likelihood | 23,248.893 | 23,249.705 | 23,248.702 | 23,248.554 | 23,252.407 |
| Akaike | −6.529 | −6.529 | −6.529 | −6.529 | −6.530 |
| Schwarz | −6.519 | −6.519 | −6.519 | −6.519 | −6.520 |
| Hannan-Quinn | −6.525 | −6.526 | −6.525 | −6.525 | −6.526 |
| Economic significance (%) | 0.056 | 0.047 | 0.114 | 0.040 | 0.071 |

Table 6 then examines whether the same relationship is visible at the monthly frequency. The monthly EGARCH-X results closely mirror the daily findings. All monthly pollen measures enter with negative coefficients and are statistically significant at least at the 10% level. The strongest effects are again found for intensity-based threshold measures, especially those capturing the frequency of high-pollen days within a month. This indicates that the volatility-reducing effect of pollen exposure is not confined to daily noise but is also visible when the data are aggregated over longer horizons. If anything, the economic magnitude is somewhat larger at the monthly level, suggesting that the effect may persist beyond the immediate daily response.

Finally, Table 7 reports additional robustness checks based on alternative samples and pollen constructions. First, the analysis is repeated separately for the Turku measurement period (1991–2014) and the Helsinki measurement period (2015–2024). Second, the total pollen series is complemented by allergenic pollen measures based on the most clinically relevant species in Finland. For allergenic pollen, the variance regressors are the threshold indicators *AP100* and *AP150*, which equal one if $AP \geq 100$ or $\geq 150$ grains m$^{-3}$, respectively, corresponding to clinically relevant exposure levels commonly used in the medical literature (Rapiejko et al., 2007).

Across all specifications, the estimated coefficients on the threshold-based pollen variables remain negative and statistically significant, confirming the robustness of the baseline findings. The effect is somewhat larger in the Helsinki subsample than in the earlier Turku subsample, but the qualitative conclusion is unchanged: elevated pollen exposure is associated with lower conditional stock market volatility.

Additional supplementary analyses reported in Internet Appendix Tables A3–A4 further examine potential transmission channels related to trading activity, market liquidity, and market-segment heterogeneity. The results indicate that the estimated pollen effect remains robust after controlling for aggregate trading activity and aggregate liquidity conditions. Moreover, the interaction specification suggests that the volatility-reducing effect associated with elevated pollen exposure weakens during periods of increased market activity, consistent with the interpretation that investor participation may represent one potential transmission channel. The appendix results further show that the documented relationship is not systematically stronger in smaller-cap market segments, although the segment-level evidence should be interpreted cautiously because direct investor-level identification is unavailable.

Additional descriptive evidence on the temporal structure and interannual variation of pollen exposure is reported in Internet Appendix Figures A1–A4. These figures demonstrate that although the timing of the pollen season is highly stable across years,

**Table 6**

EGARCH-X results with alternative covariates (monthly data without controls). Estimation results for EGARCH-X models applied to monthly logarithmic total returns of the OMX Helsinki Index. Panel A presents the mean equation, which includes monthly log returns of the DAX Performance Index as a regressor. Panel B presents the variance equation, which incorporates five alternative variance regressors. The variable $\sum TP_d$ denotes the sum of daily pollen counts within a month, while $\overline{TP_d}$ represents their monthly average. The dummy variable $TH150$ equals one if there has been at least one daily exceedance of the 150 threshold during a given month, and zero otherwise. The variable $\#Days \geq TH150$ measures the number of days within a month when the pollen count exceeded 150. Finally, the threshold indicator $\overline{TP_d} \geq 100$ equals one if the monthly average pollen count has been equal to or greater than 100, and zero otherwise. The sample consists of 344 monthly pollen observations from January 1991 to September 2024. $\lambda_1$ denotes the coefficient estimate for the pollen variable. Errors are assumed to follow a Student's $t$ distribution, and standard errors are computed using the Huber–White robust covariance estimator. Reported diagnostics include the log-likelihood, Akaike, Schwarz, and Hannan-Quinn information criteria. Economic significance is calculated as the product of the estimated pollen coefficient and the standard deviation of the pollen time series, divided by the average of the logarithm of the conditional variance series from the EGARCH-X model. $t$-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

| Coefficient | $\sum TP_d$ | $\overline{TP_d}$ | $TH150$ | $\#Days \geq TH150$ | $\overline{TP_d} \geq 100$ |
|---|---|---|---|---|---|
| Panel A: Mean equation | | | | | |
| $\alpha$ ($\times 10^3$) | 3.322* | 3.318* | 3.627** | 3.096* | 3.290* |
| | (1.819) | (1.816) | (1.996) | (1.727) | (1.791) |
| $\beta$ | 0.769*** | 0.769*** | 0.765*** | 0.759*** | 0.765*** |
| | (18.412) | (18.453) | (17.929) | (17.492) | (17.905) |
| Panel B: Variance equation | | | | | |
| $\omega$ | −0.359*** | −0.365*** | −0.425*** | −0.372*** | −0.382*** |
| | (−3.555) | (−3.583) | (−3.715) | (−3.768) | (−3.541) |
| $\alpha_1$ | 0.262*** | 0.267*** | 0.295*** | 0.278*** | 0.291*** |
| | (4.162) | (4.301) | (4.968) | (4.901) | (4.669) |
| $\gamma_1$ | −0.045 | −0.045 | −0.068 | −0.068 | −0.060 |
| | (−0.995) | (−0.989) | (−1.343) | (−1.465) | (−1.239) |
| $\beta_1$ | 0.968*** | 0.968*** | 0.956*** | 0.963*** | 0.967*** |
| | (71.093) | (69.804) | (52.148) | (66.918) | (65.170) |
| $\lambda_1^{\text{Pollen}}$ ($\times 10^3$) | −0.015** | −0.282** | −172.344** | −24.007*** | −166.408* |
| | (−2.310) | (−2.228) | (−2.078) | (−2.796) | (−1.683) |
| Log-likelihood | 580.631 | 580.411 | 580.549 | 581.756 | 579.480 |
| Akaike | −3.329 | −3.328 | −3.329 | −3.336 | −3.323 |
| Schwarz | −3.240 | −3.239 | −3.239 | −3.246 | −3.233 |
| Hannan-Quinn | −3.294 | −3.292 | −3.293 | −3.300 | −3.287 |
| Economic significance (%) | 1.709 | 1.612 | 1.384 | 1.991 | 1.215 |

both the intensity and duration of pollen exposure vary substantially over time. The appendix evidence therefore supports the interpretation that the empirical identification does not rely solely on broad seasonal differences between winter and summer periods, but also on meaningful within-season variation in pollen exposure.

Taken together, the robustness checks point to a consistent conclusion. Airborne pollen exposure has a statistically significant and economically modest negative association with Finnish stock market volatility. The finding is robust across alternative pollen measures, volatility specifications, weather controls, temporal aggregation levels, sample splits, trading-activity controls, liquidity adjustments, and alternative market segments.

At the same time, the pattern is selective enough to support a behavioral interpretation: pollen appears to matter not because it changes firm fundamentals directly, but because it may affect investor attention, participation, and short-run trading behavior. This interpretation also helps position the findings relative to the existing literature. Prior work on environmental and behavioral influences in finance typically reports effects that are statistically detectable but economically moderate (Hirshleifer and Shumway, 2003; Saunders, 1993; Pantzalis and Ucar, 2017). Our estimates fit that pattern. They do not imply that pollen is a dominant driver of market-wide volatility, but they do suggest that biologically grounded environmental shocks can contribute systematically to time-varying market risk.

The results therefore suggest that financial market volatility is shaped not only by macroeconomic news, spillovers from foreign markets, and internal volatility dynamics, but also by environmental conditions that influence human behavior. This broader perspective may be useful for future work on behavioral asset pricing, volatility forecasting, and the role of non-financial shocks in market dynamics.

## 5. Conclusions

This paper provides novel evidence that airborne pollen exposure is systematically associated with stock market volatility. Using an EGARCH-X framework applied to Finnish equity returns, we document an inverse relationship between elevated pollen levels and

**Table 7**

EGARCH-X robustness checks (daily data without controls). Estimation results from robustness tests of the EGARCH-X model are reported for two subsample periods and for two allergenic pollen thresholds. The first subsample uses Turku pollen data from January 3, 1991 to December 30, 2014 (5782 daily observations), and the second uses Helsinki pollen data from February 17, 2015 to September 27, 2024 (1337 daily observations). For these two subsamples, the variance regressor is the *Total Pollen Threshold 150 Indicator (TP150)*. The second part of the table uses the full sample (1991–2024) and the daily concentrations of *Allergenic Pollen (AP)*, defined as the sum of alder (*Alnus*), birch (*Betula*), grasses (*Poaceae*), hazel (*Corylus avellana*), and mugwort (*Artemisia vulgaris*). For a given day, an observation for each of these five allergenic plants is required, resulting in a total of 6873 observations. Here, the variance regressors are the allergenic pollen threshold indicators *AP100* and *AP150*, which equal one if $AP \geq 100$ or $\geq 150$ grains/m$^3$, respectively. Panel A reports the mean equation, where the dependent variable is the daily logarithmic total return of the OMX Helsinki Index and the regressor is the daily log return of the DAX Performance Index. Panel B reports the variance equation, with either *TP150*, *AP100*, or *AP150* as the covariate; $\lambda_1$ denotes their coefficient estimates. Errors are assumed to follow a Student's $t$ distribution, and standard errors are computed using the Huber–White robust covariance estimator. Diagnostics include the log-likelihood, Akaike, Schwarz, and Hannan-Quinn information criteria. Economic significance is measured as the product of the estimated pollen coefficient and the standard deviation of the corresponding pollen series, divided by the average of the logarithm of the conditional variance series from the EGARCH-X model. $t$-statistics are in parentheses, and ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

| Coefficient | Total Pollen *TP150* | | Allergenic Pollen *Full Sample (1991–2024)* | |
|---|---|---|---|---|
| | Turku Pollen (1991–2014) | Helsinki Pollen (2015–2024) | AP100 | AP150 |
| Panel A: Mean equation | | | | |
| $\alpha$ ($\times 10^3$) | 0.242** | 0.199 | 0.245*** | 0.247*** |
| | (2.259) | (1.368) | (2.825) | (2.848) |
| $\beta$ | 0.759*** | 0.727*** | 0.749*** | 0.749*** |
| | (67.275) | (43.055) | (76.700) | (77.615) |
| Panel B: Variance equation | | | | |
| $\omega$ | −0.102*** | −0.413** | −0.112*** | −0.112*** |
| | (−4.639) | (−2.002) | (−5.329) | (−5.320) |
| $\alpha_1$ | 0.105*** | 0.120*** | 0.111*** | 0.111*** |
| | (6.461) | (2.822) | (7.094) | (7.114) |
| $\gamma_1$ | 0.000 | −0.028 | −0.003 | −0.002 |
| | (−0.059) | (−1.533) | (−0.487) | (−0.428) |
| $\beta_1$ | 0.997*** | 0.968*** | 0.997*** | 0.997*** |
| | (723.099) | (55.411) | (780.255) | (779.480) |
| $\lambda_1^{\text{Pollen}}$ ($\times 10^3$) | −11.569** | −30.870** | −20.398** | −19.890** |
| | (−2.193) | (−2.184) | (−2.476) | (−2.043) |
| Observations | 5782 | 1337 | 6873 | 6873 |
| Mean | 0.131 | 0.265 | 0.072 | 0.054 |
| Adjusted $R^2$ | 0.408 | 0.706 | 0.429 | 0.429 |
| Log-likelihood | 18,222.654 | 5040.297 | 22,468.643 | 22,467.682 |
| Akaike | −6.300 | −7.528 | −6.536 | −6.536 |
| Schwarz | −6.291 | −7.497 | −6.528 | −6.528 |
| Hannan-Quinn | −6.297 | −7.516 | −6.533 | −6.533 |
| Economic significance (%) | 0.043 | 0.131 | 0.057 | 0.048 |

model-implied conditional volatility. The findings remain robust across alternative pollen measures, model specifications, weather controls, and subsamples.

The findings are consistent with the interpretation that pollen-induced physiological burden affects investor behavior through attention and participation channels. Periods of elevated pollen exposure may reduce investor attention, market participation, and trading activity, thereby contributing to temporarily lower market volatility.

The interaction results further suggest that the volatility-reducing effect associated with pollen exposure weakens during periods of elevated trading activity, consistent with the view that market participation represents one potential transmission channel. More broadly, the results extend prior research on environmental influences in financial markets by highlighting a physiologically grounded mechanism that differs from traditional weather-based mood proxies.

Although the estimated economic magnitude is modest, the results are economically meaningful given the persistence, predictability, and seasonal recurrence of pollen exposure. The consistency of the findings across alternative specifications and pollen measurement locations further supports the interpretation that the documented relationship is not driven solely by location-specific measurement noise.

These findings contribute to the literature on environmental influences, investor attention, and behavioral asset pricing. More generally, they suggest that environmental health-related factors may influence market dynamics in subtle but systematic ways. The results also underscore the importance of distinguishing between indirect sentiment proxies and biologically grounded environmental stressors when examining non-economic determinants of financial market behavior.

Several limitations should be acknowledged. Although the analysis exploits high-frequency variation in pollen exposure while controlling for weather conditions, calendar effects, and market variables, the findings should not be interpreted as establishing a definitive causal mechanism. In addition, the analysis focuses on Finland, where pollen exposure is both highly seasonal and economically relevant, which may limit the external validity of the results to other institutional or climatic settings.

Future research could further examine these mechanisms by exploring heterogeneity across allergen species, investor groups, and market structures. Investigating whether pollen exposure affects trading volume, liquidity, and information processing at the firm or sector level could provide additional insight into the underlying transmission channels. Extending the analysis to other countries and financial markets would also help assess the broader generalizability of the findings.

## CRediT authorship contribution statement

**Ville Kaukonen:** Writing – original draft, Writing – review & editing, Data curation, Formal analysis, Investigation, Visualization. **Mika Vaihekoski:** Conceptualization – idea, Writing – review & editing, Supervision, Validation, Data curation. **Annika Saarto:** Writing – review & editing, Data curation.

## Declaration of generative AI and AI-assisted technologies in the manuscript preparation process.

During the preparation of this work, the authors used ChatGPT, an AI language model developed by OpenAI, to assist with proofreading, text condensation, and fact-checking. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ribaf.2026.103529.

## Data availability

The authors do not have permission to share data.

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**Ville Kaukonen** is a fourth-year Ph.D. student in finance at the Turku School of Economics, University of Turku. He is writing a doctoral thesis on how Airborne Pollen can influence stock markets. ORCID: 0000-0003-0264-9332.

**Dr. Mika Vaihekoski** (corresponding author) is Professor of Finance at the Turku School of Economics, University of Turku. He has published numerous papers in finance, spanning corporate finance and asset pricing. ORCID: 0000-0002-1595-8735.

**Dr. Annika Saarto** is the Unit Manager of the Biodiversity Unit at the University of Turku. She is one of the leading experts on airborne pollen, and she published numerous articles on the topic. ORCID: 0000-0002-1568-3495.