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Abstract

The impact of strong emotions or mood on decision making and risk taking is well recognized in behavioral economics and finance. Yet, and in spite of the immense interest, no study, so far, has provided any comprehensive evidence on the impact of weather conditions. This paper provides the theoretical framework to study the impact of weather through its influence on bank manager's mood on bank inefficiency. In particular, we provide empirical evidence of the dynamic interactions between weather and bank loan inefficiency, using a panel data set that includes 69 banks operating in the US spanning the period 1994 to 2009. Bank loan inefficiency is derived using both a standard stochastic frontier production approach for bank loans and a directional distance function. Then, we employ a Panel-VAR model to derive orthogonalised impulse response functions and variance decompositions, which show responses of the main variables, weather and bank loan inefficiency, to orthogonal shocks. The results provide evidence insinuating the importance of specific weather characteristics, such as temperature and cloud cover time, in explaining the variation of gross loans.

Keywords: Bank loan inefficiency, weather conditions, panel VAR, causality, US banking.

JEL classification: G21; G28; D21.

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1. Introduction

Over the last decades, banks operate in an extremely competitive environment. According to standard financial intermediation, banks have multifold banking activities, such as lending credit and accepting deposits (Diamond, 1984; Gorton and Winton, 2003). In addition, Shleifer and Vishny (2010) argue that modern banks are also involved in other related activities, such as distributing securities, trading and borrowing money. These extra activities tend to impose additional constraints on how banking institutions are capable of allocating their capital resources into lending activities and trading activities. In an indirect fashion, such allocation decisions are related to the concept of investor sentiment, since they seem to affect stock returns. Therefore, changes in stock returns have an impact of banks' decision making related to their securitization decisions, and, thus, to their lending decisions, e.g. mortgage lending. Overall, say a downgrading (upgrading) trend in sentiments leads to lower returns (higher returns) and, in turn, to less (more) lending. Moreover, sentiments could reflect either biased expectations through the impact on the private information set or bank manager's preferences, which both could have been affected by bank manager's mood, with the latter having received influence from changing weather conditions.

Baker and Wurgler (2004) and Shleifer and Vishny (2010) claim that all of these banking activities may result in mispriced loans and a behavior that generates systematic risk. These issues seem to be highly important in a financial crisis period, since the entire spectrum of activities that the bank is involved could block or weaken the lending mechanism and, thus, transferring the problem to the real economy. Due to the credit crunch in 2008 it became all too apparent the rapidly evolving of financial markets (Moshirian, 2011) that stressed the bank performance.

In spite of the immense interest in investigating the factors affecting banks' efficiency, no study, so far, has provided any comprehensive evidence on the impact of weather conditions on such efficiency. All types of efficiency, i.e. production, cost and profit, rely on the decisions made by managers, concerning factors not known with certainty, such as the amount of output produced, the amount of inputs, input costs and prices, at all levels of the organizational structure of a bank. However, it has been shown extensively in the emotion psychology and behavioral finance literature that the decision making process and the risk taking attitudes of the banks' managers is highly affected by their mood and emotions, which, in turn, is affected by weather, situational and environmental factors. Therefore, we believe that weather induced bank managers' decisions could be reflected in the efficiency of the bank.

A potential channel that could be investigated is whether such weather conditions tend to affect the actions of the decision maker in terms of risk perceptions, processing strategies, and attention and memory. Therefore, the motivation of this research attempt could be to answer the question about what are the effects of actions of the decision maker on bank loans efficiency, while it implies an association between weather conditions and mood-influencing characteristics of bank institutions. In other words, the empirical results could suggest that weather-induced mood is a specific behavior, since weather influences mood, which, in turn, affects lending decision making and, thus, bank loans inefficiency.

Therefore, the primary goal of this empirical study is to fill this gap in the literature and to provide, for the first time, a comprehensive assessment of the association between bank inefficiency and weather conditions for the case of the U.S. banking industry, through the methodology of the panel vector autoregressive (VAR) analysis. We could also specify the various hypotheses related to bank inefficiency and explain the interaction between such inefficiency and weather conditions, yielding the following hypotheses:

Hypothesis 1: Good weather conditions, i.e. higher temperatures, lower rain and snow precipitation, and lower cloud cover time, causing positive affects to managers, are positively related to bank loans inefficiency, and/or

Hypothesis 2: Bad weather conditions, i.e. lower temperatures, higher rain and snow precipitation, and higher cloud cover time, causing negative affects to managers, are negatively related to bank loans inefficiency.

The potential explanation could be that managers, with negative affects induced by bad weather, perceive their current situation more negatively, while they believe that they are less likely to influence risky outcomes, which leads them to select less risky courses of action (Williams and Wong, 1999a), and, therefore, they are less likely to exhibit organizationally beneficial behavioral intentions (Williams and Wong, 1999b) and they move away from logical rules (Holland *et al.*, 2010), resulting overall in bank loans inefficiency.

Furthermore, weather induced mood is related to different information processing strategies (Forgas, 1995; Schwartz and Bless, 1991). Good weather inducing managers with positive affects, favor processing strategies that are simple and intuitive, use novel information, are characterized by non-conservative behavior, enhance exploratory and generative decisions and behaviors, reach decisions faster, are capable of returning to information already looked at and are in better position in evaluating external stimulus (Amabile *et al.*, 2005; Bagozzi *et al.*, 1999; Fiedler, 2001; Forgas, 2001; Fiedler, 2001; Isen *et al.*, 1982). These types of decisions enhance bank loans efficiency. According to Isen and Baron (1991), good mood might prompt managers to consider more diverse and novel alternatives in strategic decision making. These types of actions on the long run may lead to increased bank loans efficiency. By contrast, bad weather that induces negative affects to executives and decision makers prompt careful, error avoiding and conservative behavior (Fiedler, 2001) and engage to a slower and less efficient decision process (Forgas, 1989), thus, producing neutral and typical decisions that on the long run will lead to increased bank loans inefficiency.

According to Isen *et al.* (1982) and Isen and Means (1983), good mood, caused by good weather conditions and flexible decision taking that ignores information judged to be less important, leads to extreme results in the resolution of complex problems. Furthermore, Isen and Baron (1991) claim that processing strategies are affected by positive affects. Managers in weather induced good moods that use intuitive and creative processing strategies should produce more extreme performance in terms of efficiency. Bad weather induced mood managers that favor more careful and error avoiding strategies that make less use of available information in reaching their decisions (Webster *et al.*, 1996) are expected to produce more typical efficiency.

Section 2 covers the literature relevant to the mood induced decisions along with that on banks loans efficiency, while Section 3 presents the methodology of bank loan inefficiency along with that of the panel VAR modeling approach. Section 4 reports the data set used in the analysis, while Section 5 presents the empirical findings. Finally, concluding remarks and policy implications are presented in Section 6.

2. Literature review

2.1. The role of mood in decision making

The impact of strong emotions or mood on decision making and risk taking is well recognized in behavioral economics and finance (Isen and Baron, 1991; Orasanu, 1997; Peters and Slovic, 2000; Wilson, 2002). One of the fundamental questions closely related to the goal of our study, is whether mood affects the type of information individuals assess and, thus, their decision making and the adoption of successful strategies. The majority of theoretical description in the area of behavioral economics and finance account for mood affects on cognition in terms of certain basic and automatic principles, such as priming (Forgas and Bower, 1988) and accessibility (Wyer and Srull, 1986). In particular, mood theoretical approaches are described as memory models, which have to say a lot of information storage as well as the way information is actually used in decision making.

Empirical attempts show that the impact of mood on judgment and decision-making is generally pervasive, while they suggest that mood can affect human judgment and behavior, with decision makers being subject to various psychological and behavioral biases when making certain decisions, such as loss-aversion, overconfidence and mood fluctuations (Harlow and Brown, 1990; Odean, 1999; Isen, 2008). Damasio (1994) examines people with impaired ability to experience their emotions and shows that such emotions play a vital role in decision making. He also concludes that these people tend to make suboptimal decisions. When individuals form a new judgment they use their positive or negative mood as information, thus, misattributing it to the judgment target (Schwarz and Clore, 2007), while mood can color judgments through mood-congruency effects in attention and memory (Williams and Wong, 1999; Eich and Macauley, 2006). The rationale of this perspective is that decision makers that have good moods, when faced with a risky situation recall mainly the positively toned items, pay more attention on the positive items recalled and focus on the optimistic outcomes of the risky decision, whereas, decision makers with negative moods recall mainly the negative items and focus on the negative outcomes.

Within a perfect world, people are provided with enough information in reaching decisions based on logical rules. Adherence to such logical rules becomes critical in medicine, in psychology, in investments or in bank lending, i.e. decisions based on full available evidence, irrespective of personal preferences (O'Connor *et al.*, 2003). But, in such a perfect world, a logical rule is mainly the exception and not the rule. This occurs because mood can influence the extent to which individuals stick to logical rules, since, they change the way individuals process information and act upon (Holland *et al.*, 2010). Therefore, happy mood leads individuals to rely on their experiences, while sad mood leads individuals to suppress an experience-based response tendency and, thus, to move away from a logical rule and explore alternatives. According to Wright and Bower (1992), when a person has to cope with an uncertain future event, his mood may directly affect his judgment. They show that people in good mood are optimistic about future uncertain events and vice-versa. Bagozzi *et al.* (1999) also find that people in a positive-mood state are capable of evaluating external stimulus, such as life satisfaction, consumer products or even investment proposals, more positively than people in neutral- or negative-mood states. Loewenstein *et al.* (2001) provide theories linking mood and feelings to general decision-making. They develop the risk-as-feelings hypothesis, which incorporates the fact that decision makers are affected by the emotions they experience at the time of the decision. Emotional reactions to risky situations often diverge from cognitive assessments of risks and emotional reactions often drive decision making behavior.

Romer (2000), Hanock (2002) and Mehra and Sah (2002) establish the importance of emotions in economic decision-making. Forgas (1995) shows that mood strongly affects relatively abstract judgments about which people lack concrete information, such as investment appraisal decisions. Arkes *et al.* (1998) argue that emotions of individuals may influence assessments of risky decisions. They find that positive mood and emotions can foster both risk-prone behavior and risk-averse behavior, since when a positive-affect person faces a risk situation in which the potential loss is emphasized, the person demonstrates risk aversion, whereas, when the potential loss is minimized, then risk proneness is observed. If the decision maker perceives that there is a large likelihood of losses then he will avoid risk in an attempt to maintain his good feelings, otherwise, he will seek risk in an attempt to benefit from gains without fearing the negative feelings associated with loosing (Willians and Wong, 1999).

All the above issues have substantial relevance for decision making and risk. People in negative moods may choose risky options to give themselves a chance of obtaining the positive outcome that could improve their state. If negative mood leads to higher analytic processing, then the choice of the safe option may be more likely to occur or it could be directed towards a detailed assessment of the costs and benefits of the risky situations. Leith and Baumeister (1996) find that a range of induced states increase the choice of risky options, while Pietromonaco and Rook (1987) find that mild depression reduces the selection of risky options.

A different source of empirical findings comes from research on human performance. In particular, studies in decisional conflict (Hockey, 1997) argue that a range of strategy changes under stress is associated with a reduction in the amount of information used in reaching decisions. Positive mood leads individuals to organize information into larger and more effective sets and to rely more on shortcuts in judgments and decision making. Individuals who feel good, reach decisions faster, while they are capable of returning to information already looked at. Such positive mood is affected by the social characteristics of the decisions to be made, by the personal relevance of the outcome expected, and by the quality of mood (Ross and Ellard, 1986). Forgas (1989) finds that sad mood is related to a complex type of behavior, i.e. it leads to slower and less efficient decision processes, but it triggers highly motivated and selective decision strategies and information preferences, while happy mood tends to lead to faster decision processes, while it makes people ignore information judged to be less important. Webster *et al.* (1996) show that fatigued and stressed individuals make less use of available information in reaching their decisions. Finally, Hockey *et al.* (2000) show that the degree of risk taken in every decision making is affected by variations in state mood, while the strongest effects on risk behavior occur with changes in stressed type of situations.

Williams and Wong (1999a) test how mood influences managerial perceptions of risk and subsequent risk decisions. They examine whether managerial risk decisions are likely to be influenced by perceptions of the uncertainty associated with a given risk, the significance of the potential outcomes, the way in which the decision frame is perceived and whether the risks are perceived to be personally relevant. They show that managers in good moods are more likely to perceive situations in positive terms and their beliefs that they could control risky outcomes increases, while good mood increases the likelihood that managers who perceived situations as risky would choose riskier options.

Delgado-Garcia and De La Fuente-Sabate (2010) examine the influence of the affective traits of Spanish banks and savings banks CEO's on strategy and performance conformity. Affective traits refer to the long term tendencies of managers to experience positive or negative effects. They show that CEO's affective traits do influence their strategic choices. Specifically, negative affective traits lead to firm strategic conformity, whereas, positive affective traits are negatively related to strategic conformity. They also find that positive affects lead to innovative decisions and negative affects to more careful and conservative ones, a fact supported by various other studies, such as Isen (2000) and Amabile *et al.* (2005).

Lin *et al.* (2009) propose a microeconomic model of a banking firm by focusing on lending determination when sunshine induces upbeat moods. Specifically, they develop an option based model of bank behavior that integrates the weather induced managerial discretion with the bank lending considerations. Their results suggest that when a bank manager is in a good mood, his optimistic lending will result in lower default risk in equity returns. They argue that overoptimistic or more lending may cause lower risks.

Howarth and Hoffman (1984) find that performance in various mental and physical activities is correlated with humidity, sunlight and precipitation. These weather variables are usually grouped together, since they are a function of cloud cover and it is shown that good moods is associated in times of high amounts of sunlight and low cloudiness, and vice versa. According to Schwarz and Clore (1983), people tend to rate their life satisfactions much higher on sunny days than on cloudy or raining days. Rotton and Cohn (2000) conclude that high and low temperatures are related to aggression. Finally, Nastos *et al.* (2006) show that geomagnetic storms are also associated with increased level of depression and anxiety.

2.2. The role of weather conditions in finance

In the financial economics literature an interesting area of research that has evolved investigates the possible impact of weather and environmental variables on investor behavior. The main argument of these studies is that weather influences the mood of investors, which in turn influences stock returns. These studies link the mood change to either risk aversion (Kamstra et. al., 2000, 2003; Cao and Wei, 2005; Floros, 2008), misattribution (Saunders, 1993; Dichev and James, 2001; Hirshleifer and Shumway, 2003; Dowling and Lucey, 2005, 2008) or change in the investors' view of the future (Keef and Roush, 1995; Chang *et al.*, 2008). Studies in the area can be also classified into the ones that focus only on stock returns, studies that focus on stock return volatility and the ones that examine both stock returns and volatility and other market characteristics, such as trading volume and liquidity. However, the empirical evidence is to some extent mixed.

Empirical findings have shown sunshine to be positively correlated with stock returns. Saunders (1993) shows that investors' mood is upbeat or optimistic on sunny days, which uplifts the stock market returns and their pessimistic mood on cloudy days and depresses stock returns[1]. The empirical evidence of Hirshleifer and Shumway (2003) indicates that after controlling for sunshine, other weather variables, such as rain and snow, become unrelated to stock returns[2]. Finally, the sunshine effect is persistent on stock returns even with the use of intraday data and after controlling for other adverse weather conditions, such as snowiness, raininess, temperature and wind speed (Chang *et al.,* 2008)[3].

Kamstra *et al.* (2000) provide evidence that daylight savings time (DST), which is responsible for sleep desynchronosis, causes market participants to suffer greater anxiety and prefer safer investments, pushing down stock prices following a DST shift[4]. Seasonal affective disorder (SAD), which is related to longer nights in the winter time causing depression to investors, is associated with lower stock returns (Kamstra *et al.,* 2003, 2009)[5].

The psychological literature suggests that temperature is one of the three most important weather variables affecting people's mood, with the other two being sunshine and humidity (Howarth and Hoffman, 1984). Empirical findings (Cao and Wei, 2005; Floros, 2008) have shown an overall negative correlation between temperature and stock returns, while this relationship is slightly weaker in the summer than in the winter[6,7]. Furthermore, Kang *et al.* (2010) show that all three weather variables (temperature, sunshine, humidity), when examined together have an effect both on the returns and volatility of the stock market[8].

Several psychological studies, e.g. Neal and Colledge (2000), Sands and Miller (1991), associate full moon phases with depressed mood, thus, many authors hypothesize that during full moon periods stocks are valued less and returns are lower. Dichev and Janes (2001) provide evidence that the difference in returns is large between different lunar phases and exceeds the market risk premium[9]. Furthermore, Yuan *et al.* (2006) indicate and that the return difference is not due to changes in stock market volatility, trading volumes, announcements of macroeconomic indicators, major global shocks and other calendar-related anomalies[10].

The weather and environmental variables that have a strong relationship with stock market return volatility are SAD, temperature and cloudiness. Specifically, the relationship of SAD and volatility is more significant for countries furthest from the equator and small capitalization stocks (Dowling and Lucey, 2008)[11], temperature is positively correlated to the perceived risk of investors (Kaplanski and Levy, 2009)[12] and cloudiness is negatively associated with various measures of stock market volatility (Symeonides *et al.,* 2010)[13].

By contrast, there are a number of studies supporting that weather and environmental variables do not affect stock returns. Kramer and Runde (1997) show that short-term stock returns are not affected by local weather[14]. Pardo and Valor (2003) indicate that, independently of the trading system, there is no influence of weather on stock prices[15]. Tufan and Hamarat (2004) also find that weather conditions do not have any effect on stock prices[16]. Goetzmann and Zhu (2005) find no difference in the propensity to buy or sell equities on cloudy days as opposed to sunny days[17]. Jacobsen and Marquering (2008, 2009) find a strong relationship with summer-winter seasonality in stock returns which, however, cannot be linked directly to weather induced mood changes of investors[18]. Yoon and Kang (2009) show that after the 1997 financial crisis, the weather effect became insignificant[19]. Kelly and Meschke (2010) document that the SAD effect is mechanically driven by an overlapping dummy variable specification[20].

3. Theoretical methodology of measuring inefficiency

3.1 Directional technology distance function: productive bank loan inefficiency

Banks are efficient under the assumption that they are using the appropriate amounts of inputs and in the right proportions to convert them into financial products and services. It comprises a way to evaluate banking performance and separate those banks that perform well from those banks that perform poorly. In other words, it provides a numerical efficiency value and ranking of banks. As Berger and Humphrey (1997) mention, it is "*a sophisticated way to 'benchmark' the relative performance of the production units*". The performance of each bank is measured relative to what the performance of a best-practice bank on the efficient frontier would be expected to be, if it faced the same exogenous conditions as the bank being measured. There are three categories of efficiency: productive, cost and profit efficiency[21].

Following Chambers *et al.* (1996) and Färe *et al.* (2007), technology (T) for each bank is defined as the set of all feasible input-output vectors:

$$T^k = \{(x^k, y^k): x \in R_+^N, y \in R_+^M, x \text{ can produce } y\}. \quad (1)$$

where k is the number of banks and $x^k \in R_+^N$ are inputs used to produce $y^k \in R_+^M$ outputs. Given a directional vector, denoted by $g = (g_x, g_y)$, $g_x \in R_+^N$ and $g_y \in R_+^M$, that determines the direction in which technical efficiency is assessed, the directional distance function can be defined as:

$$\vec{D}_T(x, y; g_x, g_y) = \sup\{\beta : (x - \beta g_x, y + \beta g_y) \in T\}. \quad (2)$$

We choose to set $g = (g_x, g_y) = (1, 1)$ which implies that the amount by which a bank could increase outputs and decrease inputs will be $\vec{D}_T(x, y;1,1)$ units of x and y. For a bank that is technically efficient, the value of the directional distance function would be zero, while values of $\vec{D}_T(x, y, g_x, g_y) > 0$ indicate inefficient production. The directional distance function is parameterized as:

$$\vec{D}_T(x, y; g_x, g_y, t, \theta) = \alpha_0 + \sum_{n=1}^{N} \alpha_n x_n + \sum_{m=1}^{M} \beta_m y_m + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N} \alpha_{n'n} x_n x_{n'}$$
$$+ \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M} \beta_{mm'} y_m y_{m'} + \sum_{n=1}^{N}\sum_{m=1}^{M} \gamma_{mn} y_m x_n$$
$$+ \delta_1 t + \frac{1}{2}\delta_2 t^2 + \sum_{n=1}^{N} \psi_n t x_n + \sum_{m=1}^{M} \mu_m t y_m + \varepsilon \qquad (3)$$

where $\theta = (\alpha,\beta,\gamma,\delta,\mu,\psi)$ is a vector of parameters to be estimated and ε is a random error assumed to be independently and identically distributed with mean zero and variance σ_ε^2. Subtracting $\vec{D}_T(x, y; g_x, g_y, t, \theta) = u$ from both sides of (3) yields a functional form with a composite error term ε -u. The one-sided error term u represents bank-specific inefficiency and is assumed to be generated by truncation (at zero) of a normal distribution with mean μ and variance σ_u^2. The parameters of the quadratic function must satisfy a set of restrictions, including the usual restrictions for symmetry ($a_{nn'} = a_{n'n}$, $\beta_{nn'} = \beta_{n'n}$) and the following restrictions that impose the translation property:

$$\sum_{n=1}^{N} \alpha_n g_n + \sum_{m=1}^{M} \beta_m g_m = 1, \ \sum_{n=1}^{N} \alpha_{nn'} g_{x_n} = 0, \qquad n'=1,\ldots,N,$$
$$\sum_{m=1}^{M} \beta_{mm'} g_{y_m} = 0, \quad m' = 1,\ldots, M, \quad \sum_{n=1}^{N} \psi_n = 0 \text{ and } \sum_{m=1}^{M} \mu_m = 0 \qquad (4)$$

We estimate the stochastic frontier model in (3) via a maximum likelihood procedure parameterized in terms of the variance parameters $\sigma_s^2 = \sigma_u^2 + \sigma_\varepsilon^2$ and $\gamma = \sigma_u^2 / \sigma_s^2$.

3.2 Stochastic production frontier bank loan inefficiency

Following Aigner *et al*. (1977) and Meeusen and Van den Broeck (1977), the production frontier specification is:

$$Y_{it} = f(N_{it}, Z_{it}) + v_{it} + u_{it} \tag{5}$$

where Y_{it} denotes observed total gross loans for bank i at year t, N is a vector of inputs and Z is a vector of control variables, whereas, v_i corresponds to random fluctuations and is assumed to follow a symmetric normal distribution around the frontier and u_i, accounts for the individual's inefficiency that may raise loss above the best-practice level and is assumed to follow a half-normal distribution.

According to the intermediation approach (Sealey and Lindley, 1977), the bank collects funds using labor and physical capital, to transform them into loans and other earning assets. In order to measure productive inefficiency, we specify three inputs, i.e. labor, physical capital and financial capital, and one output, i.e. loans. We take into account financial capital (Berger and Mester, 1997) by including equity capital as a quasi-fixed input. In the case of the directional distance function, equity capital enters the function with a directional vector value set to zero. Control variables: the Herfindahl Index, the ratio of non-performing loans to total loans, the share of foreign-owned banks assets as a percentage of total banking assets, the capitalization ratio, the interest rate spread, the logarithm of total assets to control for size effects, the ratio of bank liquid assets to total assets at the country level to capture liquidity risk, the intermediation ratio, a measure of branch density and two macroeconomic variables, that is GDP per capita and inflation.

To empirically implement we assume that banks' bank loan function follows a translog specification:

$$\ln Y_i = \alpha_0 + \sum_i a_i \ln N_i + \sum_i \beta_i \ln Z_i + ½ \sum_i \sum_j a_{ij} \ln N_i \ln Nj +$$
$$+ \sum_i \sum_j \delta_{ij} \ln N_i \ln Z_j ++ \theta_1 t + ½ \theta_2 t^2 \sum_i \mu_i t \ln N_i + \sum_i \kappa_i t \ln Z_i + + \sum_i \nu_i t \ln N_i$$
$$+ u_i + v_i \tag{6}$$

Standard linear homogeneity and symmetry restrictions in all quadratic terms are imposed in accordance with theory, while we also include dummies to capture any differences across specific groups (clusters) of individuals and time effects. The stochastic frontier model (6) is estimated via a maximum likelihood procedure parameterized in terms of the variance parameters $\sigma_{\varepsilon}^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \sigma_u / \sigma_{\varepsilon}$.

3.3 Panel VAR Analysis

We specify a first order VAR model as follows:

$$w_{it} = \mu_i + \Phi w_{it-1} + e_{i,t},\ i = 1,\ldots,\mathrm{N},\ t = 1,\ldots,\mathrm{T}. \tag{7}$$

where w_{it} is a vector of two random variables, the bank loan inefficiency (I_{it}) and weather (W_{it}), Φ is an 2x2 matrix of coefficients, μ_i is a vector of m individual effects and $e_{i,t}$ is a multivariate white-noise vector of m residuals.

$$\begin{aligned} I_{it} &= \mu_{1i0} + \mu_{10t} + \sum_{j=1}^{J} a_{11} I_{it-j} + \sum_{j=1}^{J} a_{12} W_{it-j} + e_{1i,t} \\ W_{it} &= \mu_{2i0} + \mu_{20t} + \sum_{j=1}^{J} a_{21} I_{it-j} + \sum_{j=1}^{J} a_{22} W_{it-j} + e_{2i,t} \end{aligned} \tag{8}$$

The MA representation equates I_{it} and W_{it} on present and past residuals e_1 and e_2 from the VAR estimation:

$$\begin{aligned} I_{it} &= a_{10} + \sum_{j=1}^{\infty} b_{11j} e_{1it-j} + \sum_{j=1}^{\infty} b_{12j} e_{2it-j} \\ W_{it} &= a_{20} + \sum_{j=1}^{\infty} b_{21} j e_{1it-j} + \sum_{j=1}^{\infty} b_{22j} e_{2it-j} \end{aligned} \tag{9}$$

The orthogonalized, or structural, MA representation is:

$$\begin{aligned} I_{it} &= \alpha_{10} + \sum_{j=1}^{\infty} \beta_{11j} \varepsilon_{1it-j} + \sum_{j=1}^{\infty} \beta_{12j} \varepsilon_{2it-j} \\ W_{it} &= \alpha_{20} + \sum_{j=1}^{\infty} \beta_{21j} \varepsilon_{1it-j} + \sum_{j=1}^{\infty} \beta_{22j} \varepsilon_{2it-j} \end{aligned} \tag{10}$$

and

$$\begin{pmatrix} \beta_{11j}\beta_{12j} \\ \beta_{21j}\beta_{22j} \end{pmatrix} = \begin{pmatrix} b_{11j}b_{12j} \\ b_{21j}b_{22j} \end{pmatrix} P \begin{pmatrix} \varepsilon_{1it} \\ \varepsilon_{2it} \end{pmatrix} = P^{-1} \begin{pmatrix} e_{1it} \\ e_{2it} \end{pmatrix} \tag{11}$$

where P is the Cholesky decomposition of the covariance matrix of the residuals:

$$\begin{pmatrix} Cov(e_{1it}, e_{1it}) Cov(e_{1it}, e_{2it}) \\ Cov(e_{1it}, e_{2it}) Cov(e_{2it}, e_{2it}) \end{pmatrix} = PP^{-1} \tag{12}$$

In applying the VAR we allow for '*individual heterogeneity'* in the levels of the variables by introducing fixed effects, denoted by μ_i, in the model as in Love and Zicchino (2006) and use forward mean-differencing, *'Helmert procedure'* (Arellano and Bover, 1995). We calculate standard errors of the impulse response functions and generate confidence intervals with Monte Carlo simulations.

4. Data

A sample of 69 commercial and savings banks in four different US regions, i.e. New York (9 banks), Chicago (45 banks), Los Angeles (12 banks) and Baton Rouge (3 banks) is used. The geographical distribution was chosen so that it captures all four different types of weather characteristics across the U.S. (East, North, West and South). Balance sheet and income statement annual data is used, which is obtained from the BankScope database spanning the period 1994 to 2010.

As far as bank efficiency is concerned, total gross loans, interest expenses, personnel expenses, other operating expenses, non-interest expenses, total assets and total customer deposits are used. After reviewing the data for reporting errors and other inconsistencies, we obtain a balanced panel dataset of 759 observations coming from our 60 banking sample. We examine only continuously operating banks to avoid any possible effect from entry and exit and, thus, we focus on the performance of healthy and surviving banking institutions. Our observations come from unconsolidated data, implying that we use only the variables for the U1 code (unconsolidated statement).

Weather data comes from the AccuWeather.com site that provides detailed weather conditions for all major cities in the U.S. The measurements come as an average from different meteorological stations located in every city. In all of these stations, observations about the average temperature (in Fahrenheit degrees), the height of rain precipitation (in inches), the height of ground snow (in inches) and total sky cover (in minutes) for each day are obtained. Once all of these weather data is highly characterized by seasonality and to be certain that the empirical analysis is free of such problems, we deseasonalize our weather data set, thus, providing a conservative measure of the effect of such data. The deseasonalization was achieved by subtracting each year's mean from each daily mean. Finally, the software package RATS7 assisted the empirical analysis.

5. Empirical results

5.1 Loan inefficiency results

Table A1 in the Appendix presents the estimated parameters of the directional distance function as well as the stochastic translog production function as derived under a Stochastic Frontier Approach and shows that most of the maximum likelihood coefficients in all two equations are statistically significant.[22] The estimates of λ for all three frontiers are higher than one, suggesting that technical inefficiency, as identified within the composite error term, plays an important role in the analysis of bank performance.

Table 1 presents production stochastic and directional distance function inefficiency scores for each bank. Consistent with the literature, the overall results highlight that in general the inefficiency values derived from cost, profit as well as the directional distance functions are fairly high, indicating that banks operate far from the efficient frontier.

Table 1. Inefficiency scores across banks from directional distance function (DDF) and stochastic production function (SPF)

Bank name	SFP	DDF
Citigroup Inc	0.2789381	0.3847986
Harris National Association	0.2769125	0.2041578
Privatebancorp, Inc.	0.1740574	0.1840252
The PrivateBank and Trust Company	0.1734823	0.1316241
Wilshire State Bank	0.2057187	0.2632325
Nara Bank	0.3409816	0.3412742
Metropolitan Bank Group, Inc.	0.4211996	0.4293756
Hancock Bank of Louisiana	0.3757648	0.3425276
Shorebank Corporation, The	0.3336067	0.3954295
ShoreBank, Illinois	0.2148248	0.2336493
First Regional Bank	0.3141729	0.3514695
Preferred Bank, California	0.3780419	0.3567693
The National Republic Bank of Chicago	0.3734094	0.3960956
Broadway Bank	0.2537913	0.2600639
Lakeside Bancorp, Inc.	0.2038253	0.2408424
Lakeside Bank	0.2035535	0.2364054
Bessemer Trust Company, National Association	0.2223708	0.3645872
American Business Bank	0.2570516	0.2752761
State Bank of India (California)	0.2589424	0.3105724
Marathon National Bank of New York	0.2400071	0.2769592
Liberty Bank for Savings	0.3315355	0.3700952
Amalgamated Investments Company	0.3867632	0.4452588
Saehan Bank	0.4052286	0.4037863
Modern Bank National Association	0.3281207	0.3651096
First Savings Bank of Hegewisch	0.3321321	0.3585091
Brooklyn Federal Savings Bank	0.3681196	0.3640402
Broadway Federal Bank, FSB	0.2664702	0.3408318
North Community Bank	0.3259565	0.3393148
Albany Bank and Trust Company National Association	0.2300092	0.2415749
Archer Bank	0.2787983	0.2846366
New Century Bank, Illinois	0.3703387	0.4032464
Northeast Community Bank	0.3772297	0.3748397
Builders Bank	0.3030995	0.3679321
Asia Bank, National Association	0.2890941	0.2937902
Community Savings Bank	0.2326562	0.2384608
Community Commerce Bank	0.3745759	0.4321052
National Bank of California	0.3794562	0.4004728
Seaway Bank and Trust Company	0.4006202	0.4396188
Gotham Bank of New York	0.2445983	0.2745579
First National Banker's Bank	0.2806301	0.4167527
Hyde Park Bank and Trust Company	0.2598741	0.2784234
Metropolitan Bank and Trust Company, Illinois	0.4044868	0.4085554

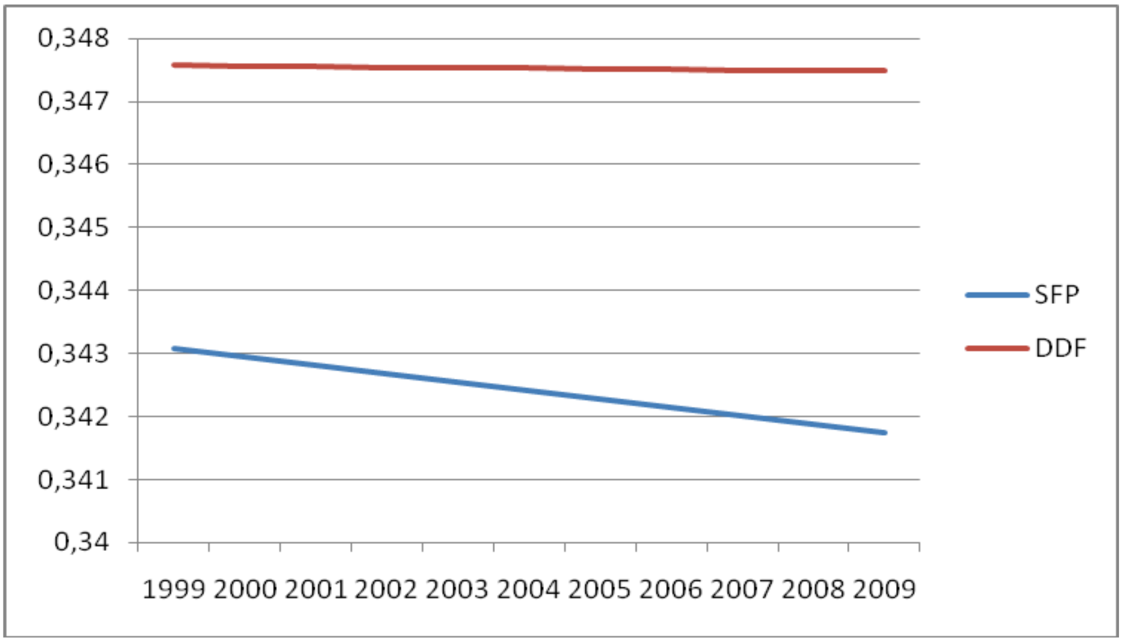
Chicago Community Bank	0.2774133	0.2980196
The First Commercial Bank	0.2876821	0.3109576
Ravenswood Bank	0.2894046	0.3257715
Austin Bank of Chicago	0.3667873	0.3877793
Delaware Place Bank	0.3693819	0.3860292
Hoyne Savings Bank	0.3674962	0.3761067
Diamond Bank FSB	0.3065434	0.3262471
Devon Bank	0.4094622	0.4602525
First Nations Bank of Wheaton	0.3480578	0.3382097
National Bank of New York City	0.3107356	0.3450534
South Central Bank, National Association	0.3698396	0.4611347
Second Federal Savings and Loan Association of Chicago	0.3822223	0.4811826
International Bank of Chicago	0.3221076	0.3187047
Park Federal Savings Bank	0.2092829	0.2765794
Lincoln Park Savings Bank	0.3478456	0.3821203
Oak Bank, Illinois	0.3301706	0.3908776
Gilmore Bank	0.3155583	0.3821117
Pacific Global Bank	0.2501579	0.2782202
Fidelity Bank	0.4101897	0.5815961
Illinois-Service Federal Savings and Loan Association	0.3039289	0.4071975
Highland Community Bank	0.2806835	0.3708227
North Bank	0.3132927	0.3917143
Central Federal Savings and Loan Association of Chicago	0.3176112	0.3704601
Eastern International Bank	0.2485438	0.3411144
American Metro Bank	0.3441479	0.3953876
Royal Savings Bank	0.2093323	0.2963079
Mutual Federal Savings and Loan Association of Chicago-Mutual Federal Bank	0.3796467	0.3779365

Note: The table presents for all bank-specific inefficiency scores.

In the case of productive inefficiency, bank's inefficiency is measured as the sum of the individual bank directional distance function estimates. It should be noted that this measure of inefficiency is based on the directional technology distance function and not on the traditional Shephard distance functions and thus, in this case a score of zero indicates that a bank is technically efficient.

Regarding the evolution of inefficiency scores over time for our entire sample (Figure 1), similar trends are observed across the two alternative inefficiency concepts. The directional distance function inefficiency exhibits a rather stable pattern though there is observable a slight downward trend. In the case of bank stochastic frontier productive inefficiency over the period under examination, there is clear evidence of a decline, albeit small in magnitude.

Figure 1. Inefficiency scores over time.



Note: SFP counts for stochastic productive bank loan inefficiency and DDF is the direction distance function inefficiency. Source: Authors' estimations.

5.2 Weather and bank inefficiency of panel VAR analysis

Prior to the estimation of the panel VAR we have to decide on the optimal lag order *j* of the right-hand variables in the system of equations (Lutkepohl, 2006). To do so, we opt for the Arellano-Bond GMM estimator for the lags of j=1,2 and 3. Results are available upon request. We use the Akaike Information Criterion (AIC) to choose the optimal lag order. The AIC suggests that the optimum lag order is one, while the Arellano-Bond AR tests confirm this. To test for evidence of autocorrelation, more lags are added. The Sargan tests show that for lag ordered one, we can not reject the null hypothesis. Therefore, we choose a VAR model of order one. The lag order of one preserves the degrees of freedom and information, given the low time frequency of our data. In addition, we perform normality tests for the residuals, opting for the Sahpiro-Francia W-test. Our results do not show violation of the normality.[23] Panel Var results are reported in Appendix (see Tables A2-A4).

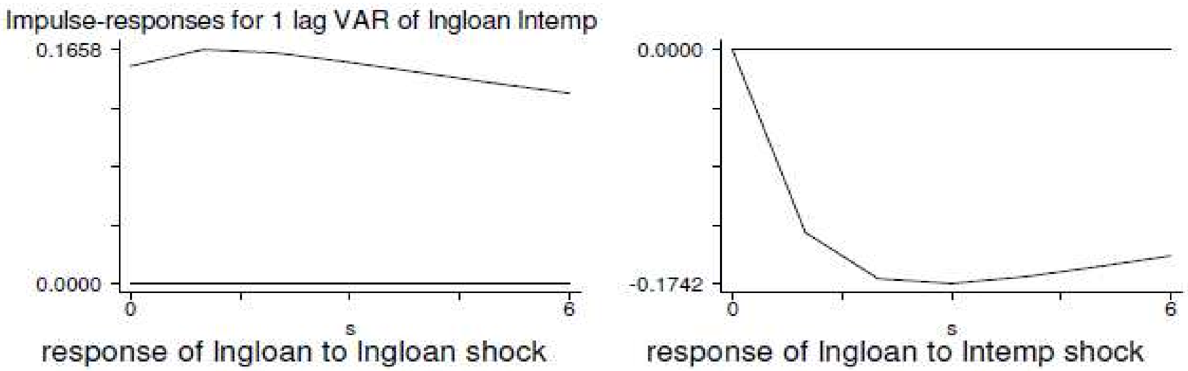
Next, we report the Impulse Response Functions (IRFs) and Variance Decompositions (VDCs) for gross loans, loans stochastic inefficiency and loans direction distance function inefficiency.

5.3 IRFs and VDCs for bank gross loans with respect to weather

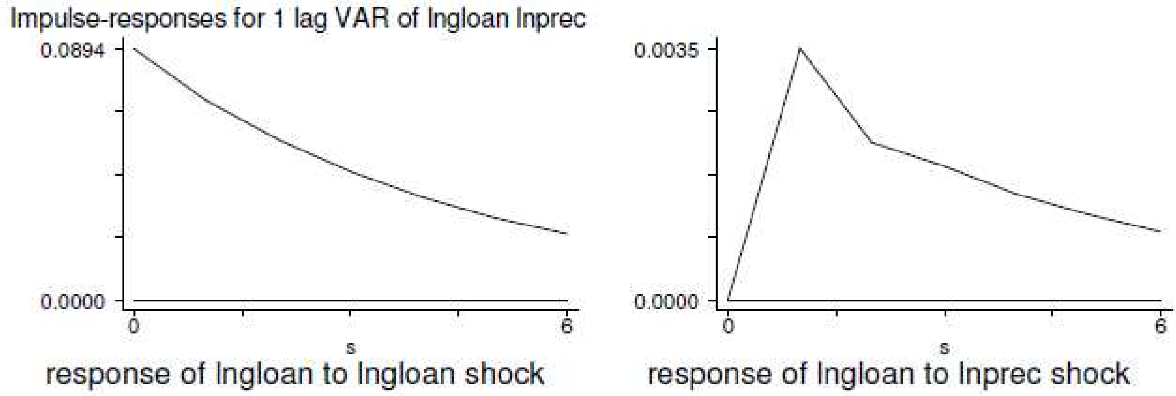
As a first step in the dynamic analysis we examine the interaction between gross bank loans and weather conditions. In the next sections, we proceed further using bank loan inefficiency scores based on the underlying optimization of direction distance function and stochastic production frontier. The IRFs derived from the unrestricted Panel-VAR are presented in diagrams below. More precisely, diagrams report the response of each variable of the VAR analysis to its own innovation and to the innovations of the other variable. Figure 2 reports the IRFs of gross loans with respect to weather conditions, i.e. temperature (lntemp), rain precipitation (lnprec), snow precipitation (lnsnowg) and cloud cover time (lncloud).

Figure 2. IRFs for gross loans with respect to weather conditions

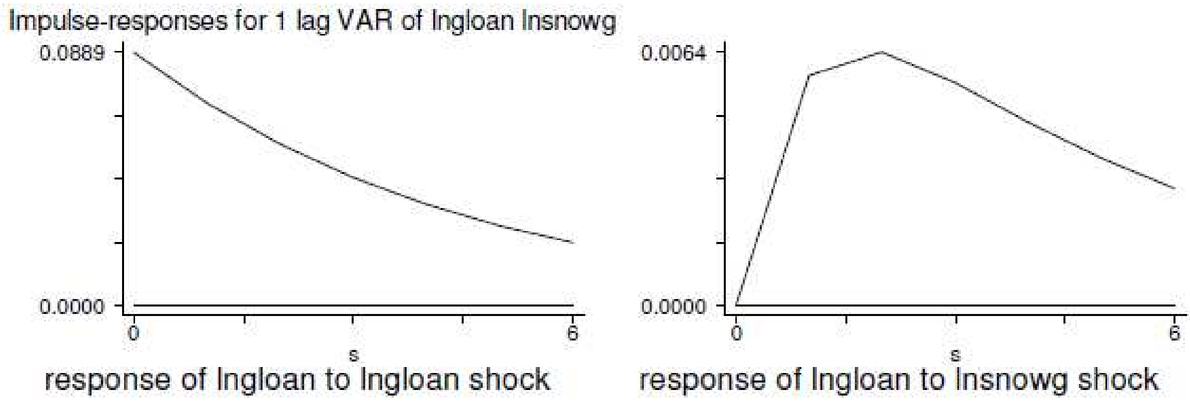
IRFs for gross loans with respect to temperature



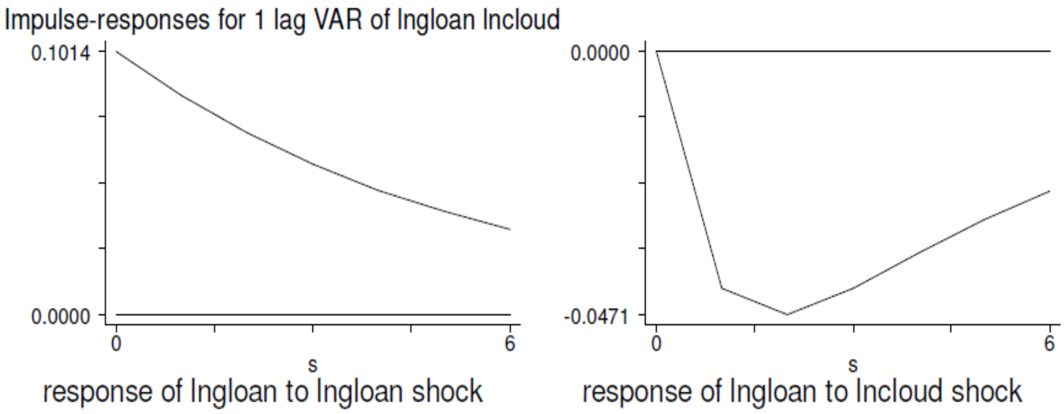
IRFs for gross loans with respect to rain precipitation



IRFs for gross loans with respect to snow precipitation



IRFs for gross loans with respect to cloud cover time



Note: lntemp counts for temperature, lnprec counts for rain precipitation, lnsnowg counts for snow, and last lncloud counts for cloud cover time.

From the first row of Figure 2 it is clear that the effect of a one standard deviation shock of temperature on gross loans is negative over time, losing power after one period. The second row reports the IRFs of gross loans with respect to rain precipitation. Figure 2 shows that the effect of a one standard deviation shock of rain precipitation on gross loans is positive over time, but less in magnitude than the impact of temperature and exhibits a sharp downward trend after one period. With respect to impact of snow to bank gross loans, we get similar impact as the one of rain precipitation, but the magnitude is smaller. That is the response of bank loans is very low in magnitude that is 0.0064.

The last row reports the IRFs of bank gross loans with respect to cloud cover time. This time the impact of one standard deviation shock of cloud cover time on bank gross loans is negative over the period, whereas it is quite small in magnitude. This result is in line with Saunders (1993), showing that investors' mood is pessimistic on cloudy days and this depresses stock returns.

To shed more light into our analysis, we also present variance decompositions (VDCs), which show the percent of the variation in one variable that is explained by the shock to another variable. We report the total effect accumulated over 10 and 20 years in Table 2. These results provide further light to IRFs, insinuating the importance of weather in explaining the variation of bank gross loans. Specifically, close to 50% of bank gross loans error variance after ten years is explained by temperature.

Moreover, the VDCs results provide further light to IRFs, insinuating that rain precipitation has limited importance in explaining the variation of bank gross loans. Specifically, less than 0.1% of gross loans error variance after ten years is explained by rain precipitation. Note that snow explains more of the gross loans error variance than any other weather variable. Overall, VDCs show that 99% of the variance of bank gross loans is explained by its own shock.

Table 2. VDCs for gross loans with respect to weather

	s	lngloan	Lntemp	lnprec	lnsnowg	lncloud
lngloan	10	0.9984	0.0001	0.0001	0.0005	0.0009
lntemp	10	0.0010	0.9978	0.0004	0.0008	0.0000
lnprec	10	0.0000	0.0004	0.9993	0.0000	0.0003
lnsnowg	10	0.0000	0.0003	0.0000	0.9993	0.0004
lncloud	10	0.0000	0.0012	0.0006	0.0012	0.9970
	s	lngloan	Lntemp	lnprec	lnsnowg	lncloud
lngloan	20	0.9985	0.0001	0.0001	0.0004	0.0009
lntemp	20	0.0001	0.9986	0.0001	0.0004	0.0008
lnprec	20	0.0001	0.0001	0.9986	0.0004	0.0009
lnsnowg	20	0.0004	0.0001	0.0001	0.9986	0.0009
lncloud	20	0.0008	0.0001	0.0001	0.0003	0.9986

Note: lntemp counts for temperature, lnprec counts for rain precipitation, lnsnowg counts for snow, and last lncloud counts for cloud cover time.

Summarizing the above results, we can see that temperature and cloud cover time have the same (negative) effect on gross loans, whereas rain and snow precipitation have the same (positive) effect. However, only temperature and cloud cover time seem to be quite important in explaining the variation of banks gross loans, as indicated by the VDC's analysis. When temperature and cloud cover time increase, then a decrease in the gross loans is obtained, implying that banks become more sensitive in issuing new loans.

Our results have some important policy implications, especially in light of the recent financial turmoil, as weather conditions could have an impact on the underlying bank sustainability as reflected by the gross loans. Our empirical findings are in line with those in the behavioral finance literature that link weather variables with mood, feelings and emotions. Specifically, Howarth and Hoffman (1984) find that temperature is one of the three most important weather variables affecting people's mood, with the other two being sunshine and humidity. Moreover, in periods of financial crisis this result enhances its significance. Baker and Wurgler (2004) and Shleifer and Vishny (2010) show that banking activities, such as pricing loans and a behavior that generate systematic risk, are very sensitive to people's mood in a financial crisis period.

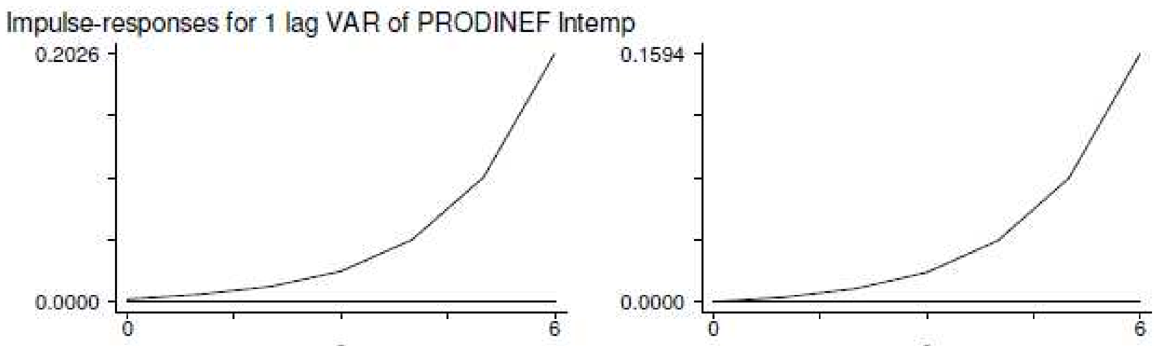
5.4 IRFs and VDCs for bank loans stochastic production inefficiency with respect to weather

From the first row of Figure 3 it is clear that the effect of a one standard deviation shock of temperature on bank loans stochastic production inefficiency is positive and also exhibits a positive trend. By contrast, the effect of a one standard deviation shock of rain precipitation is clearly positive, but it is very small in magnitude and has a bell shape type impulse on bank loan stochastic production inefficiency. Similarly, the response of bank loan stochastic production inefficiency on one standard deviation shock on snow precipitation is negligible, as depicted by the IRF below.

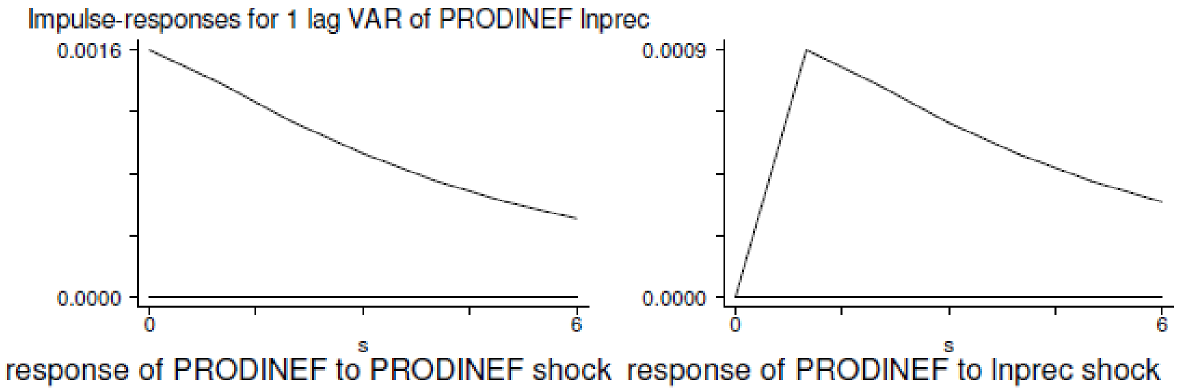
Finally, the response of bank loan stochastic production inefficiency on one standard deviation shock in cloud cover time is clearly negative, albeit not large in magnitude.

Figure 3. IRFs for bank loans stochastic production inefficiency (PRODINEF) with respect to weather conditions

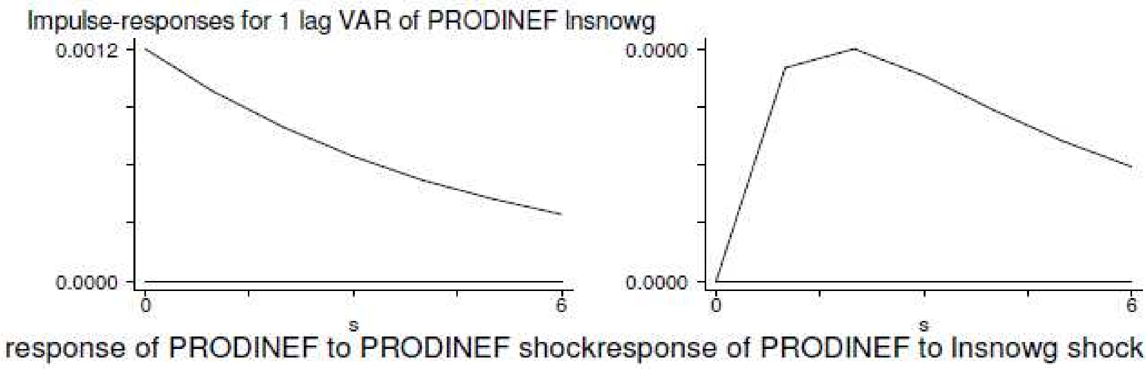
IRFs for stochastic production inefficiency with respect to temperature



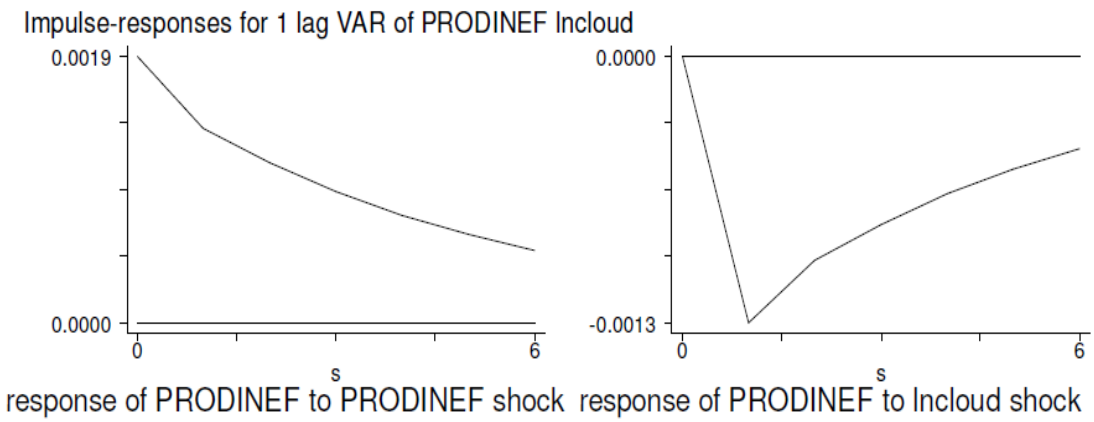
IRFs for stochastic production inefficiency with respect to rain precipitation



IRFs for stochastic production inefficiency with respect to snow precipitation



IRFs for stochastic production inefficiency with respect to cloud cover time



Note: lntemp counts for temperature, lnprec counts for rain precipitation, lnsnowg counts for snow, and last lncloud counts for cloud cover time.

To shed more light into our analysis, we also present variance decompositions (VDCs). We report the total effect accumulated over 10 and 20 years in Table 3. Specifically, 1.4% and 2.3% of bank loans inefficiency of stochastic frontier error variance after ten years is explained by temperature conditions and rain precipitation respectively. The variance of production inefficiency explained by cloud cover time and snow is quite low in magnitude.

Table 3. VDCs for bank loans stochastic production inefficiency with respect to weather conditions

	s	PRODINEF	lntemp	lnprec	lncloud	lnsnowg
PRODINEF	10	0.9617	0.0143	0.0233	0.0002	0.0006
lntemp	10	0.0040	0.9887	0.0071	0.0000	0.0002
lnprec	10	0.0161	0.0097	0.9737	0.0001	0.0004
lnsnowg	10	0.0002	0.0127	0.0208	0.9659	0.0005
lncloud	10	0.0003	0.0087	0.0146	0.0001	0.9762
	s	PRODINEF	lntemp	lnprec	lncloud	lnsnowg
PRODINEF	20	0.9670	0.0123	0.0202	0.0001	0.0005
lntemp	20	0.0112	0.9697	0.0185	0.0001	0.0004
lnprec	20	0.0195	0.0118	0.9681	0.0001	0.0005
lncloud	20	0.0001	0.0117	0.0193	0.9683	0.0005
lnsnowg	20	0.0005	0.0121	0.0199	0.0001	0.9673

Note: lntemp counts for temperature, lnprec counts for rain precipitation, lnsnowg counts for snow, and last lncloud counts for cloud cover time.

Moreover, VDCs show that the percent of the variation in bank loan stochastic production inefficiency that is explained by the shock to inefficiency is 96%, which appears to be the dominant driving force.

The VDCs table appears to confirm the above finding as only 0.0006% of the variation of bank loan stochastic production inefficiency is explained by a shock in snow.

As above, our findings show that the two most important weather factors are the ones of temperature and rain precipitation and are in line with the empirical evidence by Hirshleifer and Shumway (2003) and Chang *et al.* (2008) who indicate that sunshine is the key weather factor for influencing the trend of financial and banking variables. However, temperature is now positively correlated with banks loans stochastic production inefficiency, indicating that an increase in temperature will lead to a decrease in a banks' total efficiency. This is in line with the empirical findings by Cao and Wei (2005) and Floros (2008) that show an overall negative correlation between temperature and stock returns. The different relationship between temperature and gross loans inefficiency and temperature and banks loans productive stochastic inefficiency can be justified by the findings of Pilcher *et al.* (2002) who show that a very high temperature can cause hysteria or apathy. Furthermore, very high temperature can lead to increased levels of aggression (Palamerek and Rule, 1980; Schneider *et al.*, 1980; Bell, 1981; Howarth and Hoffman, 1984; Rotton and Cohn, 2000). According to Cao and Wei (2005), high temperature can lead both to aggression, which is associated with risk-taking and apathy as well as with risk averting, while the net impact on managers' risk taking depends on the trade-off between these two.

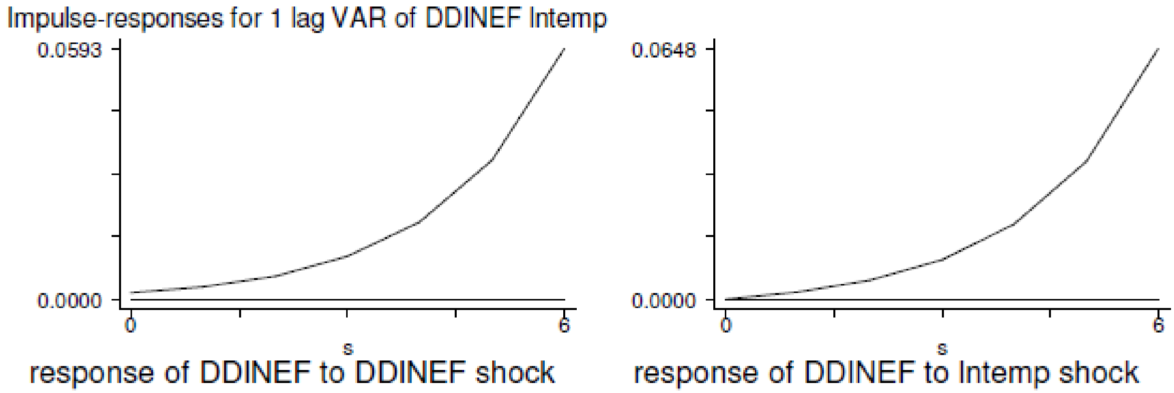
As far as the rain precipitation is concerned, we obtain the same sign as in the case of gross loans, indicating that an increase in cloud cover time will lead to an increase in the bank's total inefficiency. This is in contrast to the findings by Saunders (1983) who shows that cloud cover variables are negatively correlated with stock returns. However, according to Lerner and Keltner (2001), aggression that induces negative emotions may lead to similar action tendencies as positive emotions. Thus, high and low temperatures cannot be classified in the same category as high cloud cover, which is related to negative emotions or depression (Dowling and Lucey, 2008).

5.5 Robustness Tests: IRFs and VDCs for bank loans productive inefficiency as derived from direction distance function with respect to weather

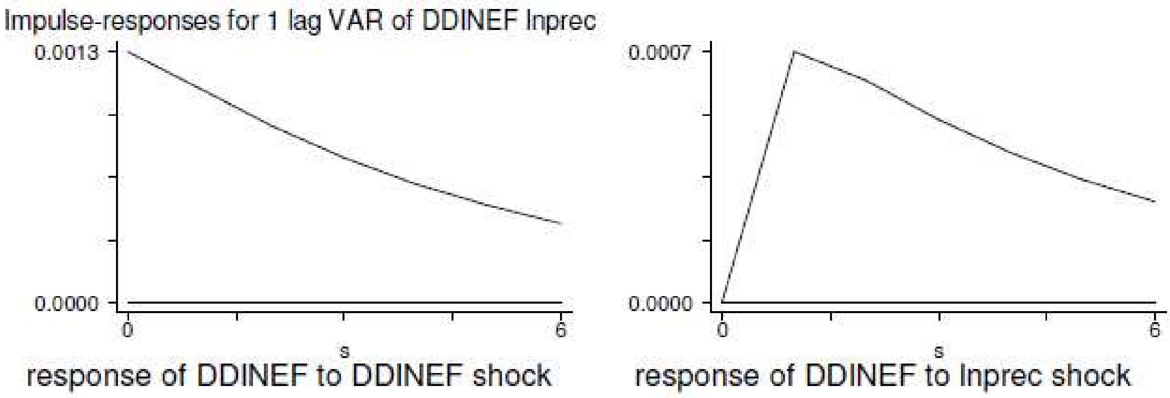
From the first row of Figure 4 it is clear that the effect of a one standard deviation shock of temperature on bank loans productive inefficiency is positive and also exhibits a positive trend, but it is low in magnitude. The effect of a one standard deviation shock of rain precipitation is clearly positive, but it is very small in magnitude and has a bell shape type, as reported earlier. By contrast, the response of bank loans productive inefficiency on one standard deviation shock of snow precipitation is zero, as depicted by the IRF below. Finally, the response of bank loans productive inefficiency on one standard deviation shock in cloud cover time is clearly negative, albeit not large in magnitude.

Figure 4. IRFs for productive inefficiency as derived from the directional distance function (DDINEF) with respect to weather conditions.

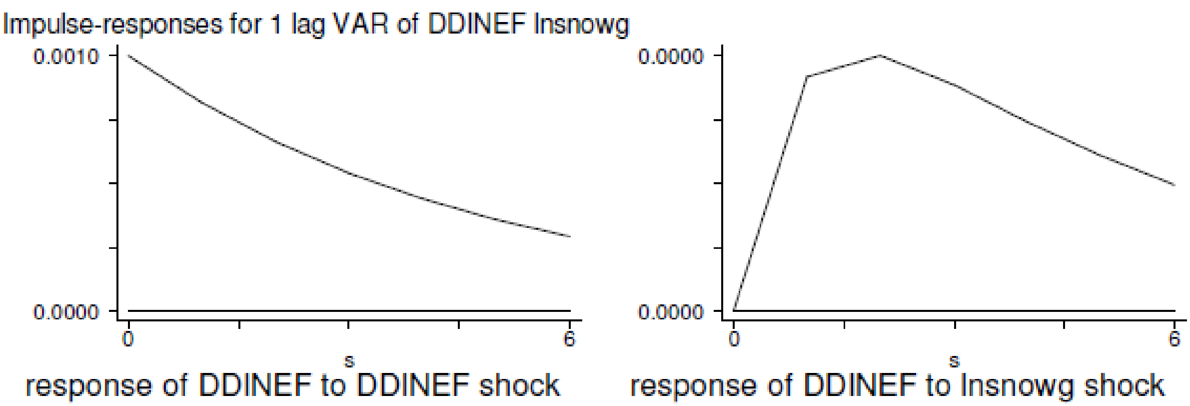
IRFs for productive inefficiency with respect to temperature



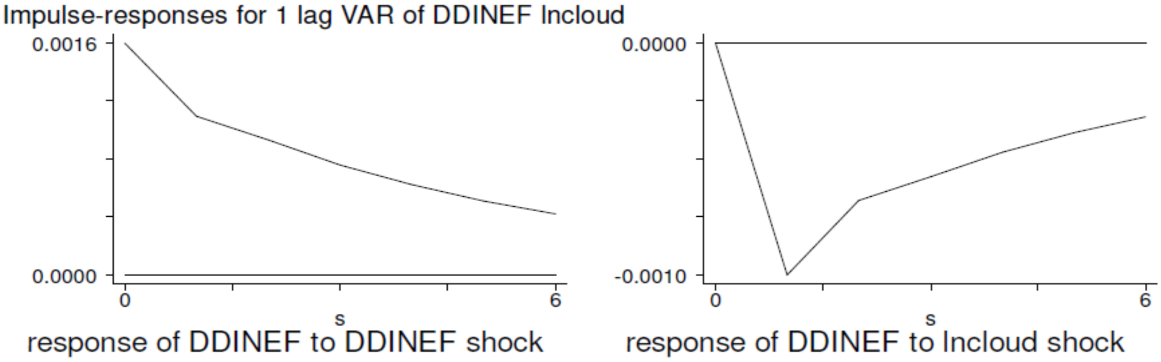
IRFs for productive inefficiency with respect to rain precipitation



IRFs for productive inefficiency with respect to snow precipitation



IRFs for productive inefficiency with respect to cloud cover time



Note: lntemp counts for temperature, lnprec counts for rain precipitation, lnsnowg counts for snow, and last lncloud counts for cloud cover time.

However, the VDCs (Table 4) show that a substantial part, that is 8% and 6.7%, of productive inefficiency variance after ten years is explained by temperature conditions and cloud cover respectively.

Table 4. VDCs for bank loans production inefficiency with respect to weather

	s	DDINEF	lntemp	lnprec	lncloud	lnsnowg
DDINEF	10	0.8338	0.0818	0.0024	0.0677	0.0144
lntemp	10	0.0964	0.8155	0.0041	0.0686	0.0155
lnprec	10	0.0043	0.0911	0.8204	0.0687	0.0155
lncloud	10	0.0699	0.0897	0.0032	0.8220	0.0151
lnsnowg	10	0.0172	0.0873	0.0039	0.0679	0.8237
	s	DDINEF	lntemp	lnprec	lncloud	lnsnowg
DDINEF	20	0.8254	0.0881	0.0028	0.0686	0.0151
lntemp	20	0.0882	0.8254	0.0028	0.0686	0.0151
lnprec	20	0.0028	0.0882	0.8254	0.0686	0.0151
lncloud	20	0.0686	0.0882	0.0028	0.8254	0.0151
lnsnowg	20	0.0151	0.0882	0.0028	0.0686	0.8254

Note: lntemp counts for temperature, lnprec counts for rain precipitation, lnsnowg counts for snow, and last lncloud counts for cloud cover time.

Moreover, VDCs show that the percent of the bank loans variation directional distance function inefficiency explained by the shock to rain precipitation is 0.0024, significant lower than the one of temperature. Nevertheless, one should not ignore such a percentage. The VDCs appear to confirm the above finding, as 0.01 of the variation of bank loans productive inefficiency is explained by a shock in snow precipitation. However, the VDCs appear to indicate that cloud cover time and temperature are quite important in explaining the variation of bank loans productive inefficiency.

These robustness tests validate the positive relationship of temperature, the negative relationship of cloud cover time and the insignificant relationship of snow and rain precipitation with banks loans productive efficiency and provide evidence, for the first time, of the role of weather conditions in the bank loans efficiency.

6. Concluding remarks and policy implications

Bank loans efficiency seems to be one of the most important 'assets' for banks and is given priority over the last decades, because banks operate in an extremely competitive environment, where survival has become uncertain. In this paper, bank efficiency across US banking has been estimated over the period 1994-2010, using the translog function. These efficiency estimates are then used in the second part of the analysis, which examines the impact of certain weather conditions on bank loans inefficiency.

A panel-VAR model along with the methodology of GMM and through impulse response function and variance decompositions, showed that the impact of a shock on temperature on gross bank loans inefficiency is negative over time, though it does not exhibit persistence. By contrast, the impact of precipitation and snow on this gross loans inefficiency is positive, though small in magnitude. Interestingly, when we estimate the banks loan inefficiency, either through the direction distance function or the stochastic frontier analysis, the one standard deviation shock of the temperature on inefficiency is positive and also exhibits a positive trend. This is in line with the empirical findings by Pilcher *et al.* (2002), Cao and Wei (2005) and Floros (2008), reporting negative correlation between temperature and stock returns. It appears that high temperature could lead to increased levels of aggression (Palamerek and Rule, 1980; Schneider *et al.*, 1980; Bell, 1981; Howarth and Hoffman, 1984; Rotton and Cohn, 2000) that in turn contribute to risk taking activities that raise bank inefficiency. Similarly, the same results were obtained for the case of the one standard deviation shock of precipitation and snow, whereas the impact of cloud cover time is negative.

The results receive high importance due to their implications about the efficiency of the monetary policy to pump out liquidity into the real economy. Therefore, certain weather conditions, such as temperature and cloud cover time, could increase bank loans inefficiency and to make stronger the capacity of the central bank through the bank lending channel, to stabilize the economy. Further research on this field would include banking systems from different groups of countries, which might contribute to the robustness of results.

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Appendix

Table A1. Stochastic Production Frontier (SPF) and Direction Distance Function (DDF) estimates

	SPF			DDF	
	Coef.	*p-value*		*Coef.*	*p-value*
$\ln x_1$	0.706	0.000	**$\ln x_1$**	0.899	0.000
$\ln x_2$	0.129	0.000	**$\ln x_2$**	-0.057	0.000
$\ln x_3$	-0.087	0.121	**$\ln x_3$**	0.479	0.000
$\ln x_1^2$	-0.108	0.000	**$\ln x_1^2$**	-0.031	0.000
$\ln x_2^2$	-0.108	0.000	**$\ln x_2^2$**	0.000	0.372
$\ln x_3^2$	0.108	0.000	**$\ln x_3^2$**	-0.015	0.000
$\ln x_1 x_2$	0.068	0.002	**$\ln x_1 x_2$**	0.001	0.000
$\ln x_1 x_3$	-0.102	0.000	**$\ln x_1 x_3$**	0.021	0.000
$\ln x_2 x_3$	-0.059	0.000	**$\ln x_2 x_3$**	-0.002	0.000
t	0.032	0.374	**t**	0.096	0.000
t^2	-0.007	0.163	**t^2**	-0.018	0.000
$t\ln x_1$	-0.012	0.001	**$t\ln x_1$**	0.042	0.000
$t\ln x_2$	0.012	0.001	**$t\ln x_2$**	0.000	0.000
$t\ln x_3$	0.002	0.619	**$t\ln x_3$**	-0.049	0.000
lnTA	0.236	0.000			
Constant	0.451	0.000	**Constant**	0.333	0.000
Log likelihood	859.737			-874.692	
σ_v^2	0.013			0.031	
σ_u^2	0.014			0.335	
Obs	759			759	

Note:. Standard errors were obtained by bootstrapping with 100 replications. Standard homogeneity and symmetry restrictions are imposed, thus coefficients of interaction terms. Bank dummy variables are included to capture heterogeneity. One bank dummy is excluded in order to avoid perfect collinearity.

Table A2. Panel-Var GMM estimations for Gross Loans (lngloan).

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number of observations used : 621

EQ1: dep.var : h_lngloan

	b_GMM	se_GMM	t_GMM
L.h_lngloan	.41278726	.38420393	1.0743963
L.h_lntemp	-3.4955188	3.6017026	-.97051845
L.h_lnprec	.02152566	.18885488	.11397988
L.h_lnsnowg	.14698083	.11207975	1.311395
L.h_lncloud	-1.5488697	1.545725	-1.0020344

EQ2: dep.var : h_lntemp

	b_GMM	se_GMM	t_GMM
L.h_lngloan	-.04838912	.08925884	-.54212135
L.h_lntemp	.47133505	.84655338	.55676944
L.h_lnprec	.03723365	.04446764	.83732017
L.h_lnsnowg	-.0678181	.02205868	-3.0744407
L.h_lncloud	.14666749	.35887146	.40869088

EQ3: dep.var : h_lnprec

	b_GMM	se_GMM	t_GMM
L.h_lngloan	-.23200876	.31456033	-.73756524
L.h_lntemp	-3.6291912	2.976017	-1.2194793
L.h_lnprec	-.08304991	.16268185	-.51050507
L.h_lnsnowg	-.21275431	.07637005	-2.7858345
L.h_lncloud	-.65872424	1.2493755	-.52724281

EQ4: dep.var : h_lnsnowg

	b_GMM	se_GMM	t_GMM
L.h_lngloan	-.14093182	.26485949	-.53210032
L.h_lntemp	.65060319	2.418806	.26897701
L.h_lnprec	.77798604	.1287881	6.0408226
L.h_lnsnowg	.37408893	.08011186	4.6695823
L.h_lncloud	.18804647	1.0751724	.17489889

EQ5: dep.var : h_lncloud

	b_GMM	se_GMM	t_GMM
L.h_lngloan	.00116767	.12799413	.00912286
L.h_lntemp	.660671	1.2090475	.54643924
L.h_lnprec	.22022236	.0642172	3.429336
L.h_lnsnowg	.06032617	.03159173	1.9095557
L.h_lncloud	.47339691	.49148037	.96320614

just identified - Hansen statistic is not calculated

symmetric uu[5,5]

	lngloan	lntemp	lnprec	lnsnowg	lncloud
lngloan	.02593946				
lntemp	-.00255378	.00140485			
lnprec	.01587359	-.00262427	.01578484		
lnsnowg	.00067807	-.00014212	-.00201005	.02014471	
lncloud	-.0046044	.00057172	-.00384691	.00129115	.00260673

Residuals correlation matrix

	u1	u2	u3	u4	u5
u1	1.0000				
u2	-0.4229	1.0000			
	0.0000				
u3	0.7845	-0.5568	1.0000		
	0.0000	0.0000			
u4	0.0303	-0.0289	-0.1115	1.0000	
	0.4504	0.4715	0.0054		
u5	-0.5599	0.2978	-0.5994	0.1769	1.0000
	0.0000	0.0000	0.0000	0.0000	

Note:. Method of estimation is GMM. Lag order is one. Standard errors were obtained by bootstrapping with 100 replications. Standard homogeneity and symmetry restrictions are imposed, thus coefficients of interaction terms. Bank dummy variables are included to capture heterogeneity. One bank dummy is excluded in order to avoid perfect collinearity.

Table A3. Panel-Var Stochastic Production Frontier Bank Inefficiency (PRODINEF).

```
EQ1: dep.var      : h_PRODINEF

                        b_GMM         se_GMM          t_GMM
  L.h_PRODINEF      .23572718      .85568204      .27548455
  L.h_lntemp      9.378e-09     2.413e-08     .38870528
  L.h_lnprec      2.032e-09     9.935e-09     .20457264
 L.h_lnsnowg     -6.903e-10     5.093e-09    -.13555179
 L.h_lncloud     -1.008e-09     1.155e-08    -.08728834
------------------------------------------------------------------
------------------------------------------------------------------
EQ2: dep.var      : h_lntemp

                        b_GMM         se_GMM          t_GMM
  L.h_PRODINEF     -357721.91     1573352.3    -.22736287
  L.h_lntemp      .93184714     .11878433     7.8448661
  L.h_lnprec      .06161289     .03508006     1.7563508
 L.h_lnsnowg     -.07362078     .02330793    -3.1586155
 L.h_lncloud      .32989067     .10388038     3.1756783
------------------------------------------------------------------
------------------------------------------------------------------
EQ3: dep.var      : h_lnprec

                        b_GMM         se_GMM          t_GMM
  L.h_PRODINEF     -685663.68     2240928.1    -.30597308
  L.h_lntemp     -1.4340848     .14959813    -9.5862477
  L.h_lnprec      .02375137     .04401184     .53965871
 L.h_lnsnowg     -.24822087     .02633292    -9.4262558
 L.h_lncloud      .23968476     .11214354     2.1373034
------------------------------------------------------------------
------------------------------------------------------------------
EQ4: dep.var      : h_lnsnowg

                      b_GMM        se_GMM         t_GMM
  L.h_PRODINEF    2514626.1    4708351.9    .53407778
  L.h_lntemp    1.9473127    .43696631    4.4564367
  L.h_lnprec     .81413777    .09854718    8.2614007
 L.h_lnsnowg    .33077904    .06637548    4.9834519
 L.h_lncloud    .79048923    .19139022    4.1302489
------------------------------------------------------------------
------------------------------------------------------------------
EQ5: dep.var      : h_lncloud
                    b_GMM        se_GMM        t_GMM
  L.h_PRODINEF   -406846.47    1747561.7    -.23280807
 L.h_lntemp     .65475911    .13049747    5.0174086
 L.h_lnprec     .22370559    .03838849    5.8274133
L.h_lnsnowg    .06355147    .02776707    2.2887353
L.h_lncloud    .46093687    .10416048    4.4252568
------------------------------------------------------------------
just identified - Hansen statistic is not calculated

symmetric uu[5,5]
              inef1        lntemp        lnprec       lnsnowg      lncloud
   inef1   7.139e-17
  lntemp   2.156e-12     .00239551
  lnprec  -1.636e-11    -.00154912     .00336282
 lnsnowg   1.481e-10     .00165934    -.00390273     .02292571
 lncloud  -9.966e-12     .00111735    -.00118641     .00274239    .00260872

Residuals correlation matrix

             |       u1        u2        u3        u4        u5
-------------+--------------------------------------------------
          u1 |   1.0000
             |
          u2 |   0.0050    1.0000
             |   0.9019
             |
          u3 |  -0.0333   -0.5455    1.0000
             |   0.4079    0.0000
             |
          u4 |   0.1156    0.2221   -0.4441    1.0000
             |   0.0039    0.0000    0.0000
             |
          u5 |  -0.0233    0.4462   -0.4002    0.3536    1.0000
             |   0.5622    0.0000    0.0000    0.0000
```

Note:. Method of estimation is GMM. Lag order is one. Standard errors were obtained by bootstrapping with 100 replications. Standard homogeneity and symmetry restrictions are imposed, thus coefficients of interaction terms. Bank dummy variables are included to capture heterogeneity. One bank dummy is excluded in order to avoid perfect collinearity.

Table A4. Panel-Var GMM estimations
Direction Distance Function Bank Inefficiency (DDINEF).

```
EQ1: dep.var       : h_DDINEF

                   b_GMM        se_GMM        t_GMM
  L.h_DDINEF   .23781464    .86381479    .27530744
 L.h_lntemp   1.004e-08    2.505e-08    .40093313
 L.h_lnprec   1.864e-09    1.020e-08    .18275817
L.h_lnsnowg  -6.172e-10    5.590e-09   -.11041463
L.h_lncloud  -2.057e-09    1.167e-08   -.17628963
-----------------------------------------------------
-----------------------------------------------------
EQ2: dep.var       : h_lntemp

                   b_GMM        se_GMM        t_GMM
  L.h_DDINEF  -356881.19    1590329.5   -.22440708
 L.h_lntemp    .93224336    .11909704    7.8275946
 L.h_lnprec    .06169993    .03534937    1.7454321
L.h_lnsnowg   -.07338873    .02386641   -3.0749806
L.h_lncloud    .32905233    .10486163    3.1379668
-----------------------------------------------------
-----------------------------------------------------
EQ3: dep.var       : h_lnprec

                   b_GMM        se_GMM        t_GMM
  L.h_DDINEF  -701569.24    2274162.9    -.3084956
 L.h_lntemp   -1.433086     .15027696   -9.5362992
 L.h_lnprec    .02409454    .04447651    .54173639
L.h_lnsnowg   -.24763432    .02724142   -9.0903601
L.h_lncloud    .23769699     .1134766    2.0946785
-----------------------------------------------------
-----------------------------------------------------
EQ4: dep.var       : h_lnsnowg
                   b_GMM      se_GMM       t_GMM
  L.h_DDINEF   2572530.1     4805995   .53527522
 L.h_lntemp    1.9436559   .43766603   4.4409567
 L.h_lnprec    .81288353   .09958154   8.1629946
L.h_lnsnowg    .32863138   .06801802   4.8315338
L.h_lncloud    .79776993   .19494101   4.0923657
-----------------------------------------------------
-----------------------------------------------------
EQ5: dep.var       : h_lncloud

                   b_GMM        se_GMM        t_GMM
  L.h_DDINEF  -408607.49    1767012.7   -.23124196
 L.h_lntemp    .65524687      .130919    5.0049792
 L.h_lnprec    .22383193    .03868827    5.7855246
L.h_lnsnowg    .06383737    .02827303     2.257889
L.h_lncloud    .45992432    .10504973     4.378158
-----------------------------------------------------
just identified - Hansen statistic is not calculated

symmetric uu[5,5]
              inef2        lntemp        lnprec       lnsnowg       lncloud
   inef2  7.237e-17
  lntemp  2.493e-12     .00239517
  lnprec -1.935e-11    -.00154892     .00336523
 lnsnowg  1.569e-10     .00166189    -.00390427     .02290457
 lncloud -1.199e-11     .00111752    -.00118468     .00273995     .00260967

Residuals correlation matrix

             |       u1        u2        u3        u4        u5
-------------+--------------------------------------------------
          u1 |   1.0000
             |
          u2 |   0.0057    1.0000
             |   0.8870
          u3 |  -0.0391   -0.5453    1.0000
             |   0.3310    0.0000
          u4 |   0.1217    0.2226   -0.4443    1.0000
             |   0.0024    0.0000    0.0000
          u5 |  -0.0278    0.4462   -0.3994    0.3534    1.0000
             |   0.4891    0.0000    0.0000    0.0000
             |
```

Note:. Method of estimation is GMM. Lag order is one. Standard errors were obtained by bootstrapping with 100 replications. Standard homogeneity and symmetry restrictions are imposed, thus coefficients of interaction terms. Bank dummy variables are included to capture heterogeneity. One bank dummy is excluded in order to avoid perfect collinearity.

Endnotes

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[1] Saunders (1993) is the first to link investment behavior to weather conditions. He uses meteorological data from the City of New York and stock market data for the Dow Jones Industrial Average (DJIA) and the NYSE/AMEX index from 1927 to 1989. The weather variable that he uses is the cloud cover, because it is highly influential on mood. The methodology, firstly, pairs data percentage cloud cover with data on stock price indices returns on a daily basis. Then the mean percentage daily change and the frequency of positive daily change are calculated for each of the indices. Secondly, the daily index return is regressed against a month dummy, a day dummy, a cloud cover variable and a lagged return variable. The day and moth dummies control for possible seasonal anomalies and the lagged return accounts for non-synchronous trading effects. His empirical evidence suggests that less cloud cover is associated with higher returns and the return difference between the cloudiest days and the least cloudy days is statistically significant.

[2] Hirshleifer and Shumway (2003) examine the relationship between cloud cover in the city of a country's leading stock exchange and daily market index returns across 26 stock markets around the globe for the period of 1982–1997. They calculate the average cloudiness value for each week of the year in each city and deseasonalize by subtracting each week's mean cloudiness from each daily mean. Their methodology involves univariate regressions of returns against the cloudiness measure for each city, logit models of maximum likelihood, pooled regressions with data from all cities and a city-specific fixed effects model with panel corrected standard errors. Their empirical evidence shows that sunshine is highly correlated with stock returns, in line with Saunders (1993).

[3] Chang *et al.* (2008), instead of using daily returns as previous studies, focus on the relation between cloud cover and intraday returns and trading patterns of New York Stock Exchange stocks from 1994 to 2004. Trading patterns are captured by trading volume, bid-ask spread, quoted depth, return volatility and order imbalance. The volatility estimation based on the range of the intraday prices and on the basis of the standard deviation of the bid-ask mid-point returns. All weather variables are deseasonalized by subtracting its average value of each calendar week (Hirshleifer and Shumway, 2003). They regress stock returns and each trading variable on cloud cover, while controlling for other adverse weather conditions such as snowiness, raininess, temperature and wind speed. They show that cloudiness has a significant influence on stock returns, only at the market open, a significant positive effect on intraday volatility and a negative effect with market depth over the entire trading day.

[4] Kamstra et al. (2000) examine the empirical association between daylight savings time (DST) and stock market returns. They use stock market data from the US, Canada, UK and Germany from 1928 to 1998 and calculate the mean of daily returns following a DST shift in fall and spring, a weekend and on all other normal days. They find that the magnitude of the DST to be roughly 200 to 500 percent of the regular weekend effect, which is both statistically and economically significant.

[5] Kamstra *et al.* (2003) are the first to examine the seasonal affective disorder (SAD) on stock market returns with data from ten countries from 1928 to 2000. The authors assume that longer nights should be associated with lower stock returns due to the SAD effect or "winter blues", since depression caused by longer nights leads to higher risk aversion. The SAD measure is calculated as the number of hours of night during fall and winter at each stock exchange. They regress returns on up two lagged returns, a Monday dummy, a dummy variable for a tax-loss selling effect, the SAD measure, a fall dummy and three control weather variables (cloud cover, precipitation and temperature). Their evidence suggests the existence of an important effect of SAD on stock market returns that is confirmed for many international markets.

[6] Cao and Wei (2005) investigate the relationship between temperature and stock market returns using data from eight financial markets located in the US, Canada, UK, Germany, Sweden, Australia, Japan and Taiwan from 1962 to 2001. The rationale of their research is that temperature affects human behavior, since extreme temperatures may lead to aggression and more specifically high temperatures can also lead to apathy. They test the hypothesis that lower temperatures are associated with higher stock returns due to aggressive risk taking and higher temperatures can lead to higher or lower stock returns, depending on which mood, aggression (risk-taking) or apathy (risk avoidance) dominates. They follow the methodology of Saunders (1993) by grouping returns according to temperature ordering and Hirshleifer and Shumway (2003) and Kamstra *et al.* (2003) by performing regression analysis to quantify the precise linkage between the two variables, while controlling for other known market anomalies. They find that a statistically significant, overall negative correlation exists between temperature and stock returns, while this relationship is slightly weaker in the summer than in the winter. Their findings remain robust even after controlling for the geographical dispersion of investors relative to the city where the stock exchange.

[7] Floros (2008) re-examines the empirical link between temperature and stock market returns using a data sample from Europe (Austria, Belgium, France, Greece and UK) from 1995 to 2005. He extends previous literature by using a GARCH model and finds a negative relationship between temperature and stock market returns for Austria, Belgium and France, in line with the findings of Cao and Wei (2005).

[8] Kang *et al.* (2010) examine the relationship between stock market returns and volatility and three specific weather variables (temperature, humidity, and sunshine) using the Shanghai A- and B-share indices and daily data from 1996 to 2007. They follow the methodology of Yoon and Kang (2009) and convert the three weather variables into dummy variables, because they contain a seasonal factor, by using the 21-day and 31-day moving average and moving standard deviation. They regress the daily return of the two indices against dummy variables for know calendar anomalies and dummy variables for weather conditions and weather interaction effects. Furthermore, they use a simple GARCH model to capture time-varying volatility. They find that weather has an effect on the returns and volatility of the Shanghai stock market, indicating that various weather conditions affect investor's decisions making.

[9] Dichev and Janes (2001) examine if lunar phases affect stock returns, stock returns volatility and trading activity for 25 different countries and a time period of 100 years for the US and 30 years for all other countries. They find that returns around new moon dates are about double the returns around full moon dates. The difference in returns is large and in most cases it exceeds the market risk premium. However, they fail to find evidence indicating a relationship between lunar phases and return volatility or trading activity.

[10] Yuan *et al.* (2006) also investigate the relationship between lunar phases and stock market returns of 48 countries globally from 1973 to 2001. They follow the evidence and argument in Hirshleifer and Shumway (2003) that good mood is associated with high asset returns. Their methodology involves first the calculation of stock returns in full moon and new moon phases. A sinusoidal model is also estimated to test for the cyclical pattern of the lunar effect and a pooled regression is estimated with panel corrected standard errors for all 48 countries and three subgroups. Finally, they examine if the effect on stock returns is related to stock size. Their findings indicate that stock returns are lower on the days around a full moon than on the days around a new moon. The return difference is statistically and economic significant and is not due to changes in stock market volatility, trading volumes, announcements of macroeconomic indicators, major global shocks, other calendar-related anomalies such as the January effect, the day-of-week effect, the calendar month effect, and the holiday effect (including lunar holidays).

[11] Dowling and Lucey (2008) examine the empirical effect of seven mood-proxies (SAD, DST, Wind, Temperature, Precipitation, Lunar Phases, Geomagnetic storms) on both the returns and variances of 37 national equity market indices and 21 small capitalization indices. Their methodology involves GARCH-type processes to approximate and model the variations in the conditional variance of returns. They show that SAD has the most significant relationship with both equity returns and volatility and that this relationship is more significant for countries furthest from the equator and for small capitalization stocks. For all other mood measures there is at best a weak relationship between them and equity returns and variance.

[12] Kaplanski and Levy (2009) consider the effect of SAD and temperature on the VIX option's implied volatility index (Fear Index), which is traded in the Chicago Board Options Exchange (CBOE) and measure the perceived risk of investors. They use also a measure of so-called 'actual' volatility, based on the historical standard deviation of a monthly window of daily returns. Their empirical findings show that the number of daylight hours is negatively related only to the 'perceived' volatility proxied by the VIX and not to the 'actual' historical volatility measure, while temperature is positively correlated to the perceived risk of investors.

[13] Symeonides *et al.* (2010) investigate the empirical association between stock market volatility, in all three forms (historical, implied and realized), and investor mood-proxies, related to the weather and the environment. These are sky cover, temperature, precipitation and the variation in the number of hours of night, i.e. seasonal affective disorder (SAD). They consider the effect of absolute deviations from

seasonal norms and of dummies which reflect extreme weather conditions. They use an ARCH-type model on the dataset of Hirshleifer and Shumway (2003), which consists of stock market index returns for 26 stock exchanges internationally between 1982 and 1997, for the historical volatility effects. The implied volatility is proxied by four implied volatility indices for the CBOE along with the term structure of the VIX volatility index, whereas, the realized volatility is constructed on the basis of high-frequency returns for the S&P500 index. Their results suggest that SAD and cloudiness are negatively associated with various measures of stock market volatility and that the effect depends on the location of a city on Earth with respect to the equator. Finally, their evidence did not show any explanatory power of absolute deviations of variables from seasonal norms and dummies related to extreme weather conditions.

[14] Kramer and Runde (1997) replicate the study of Saunders (1993), using data from the Frankfurt stock exchange from 1960 to 1990 and as weather variables cloud cover, relative humidity and atmospheric pressure. They find both a positive and negative effect of weather on stock returns depending upon the test procedure adopted, indicating that short-term stock returns are not affected by local weather.

[15] Pardo and Valor (2003) investigate the relationship between sunshine hours and humidity levels and market index returns with the use of data from Spain from 1981 to 2000. The daily returns of the stock index are separated into sunshine hours and relative humidity quintiles. The research hypothesis is tested both on an open outcry trading system and a screen traded environment. Their evidence indicates that, independently of the trading system, there is no influence of weather on stock prices.

[16] Tufan and Hamarat (2004) find that weather conditions do not have any effect on stock prices. Specifically, they examine the relationship between cloud cover and the return of the Turkish stock exchange index from 1987 to 2002. In contrast to other studies, they apply the Kruskal Wallis test at quintiles formed on cloudiness.

[17] Goetzmann and Zhu (2005) use a large panel database of individual investor accounts from 6 major cities of the US from 1991 to 1995, instead of aggregate market data, to examine if emotion influences decision-making. They calculate the daily cloudiness in a manner similar to Hirshleifer and Shumway (2001) and buy and sell imbalance (BSI), in a way similar to Hong and Kumar (2002) and Zhu (2002). They regress the cloudiness measure against the BSI and total trading volume. They find no difference in the propensity to buy or sell equities on cloudy days as opposed to sunny days. Furthermore, they find that the bid-ask spread widens on cloudy days and when they control for this effect the weather variable becomes smaller and insignificant.

[18] Jacobsen and Marquering (2008) use monthly returns on the value weighted indices of Morgan Stanley Capital International (MSCI) representing 48 different countries from 1970 to 2004 to re-examine the relationship between SAD, temperature and stock returns identified by Kamstra *et al.* (2003) and Cao *et al.* (2005). They find a strong relationship with summer-winter seasonality in stock returns which, however, cannot be linked directly to weather induced mood changes of investors. They

identify other variables that can explain this seasonality, such as the Sell in May/Halloween variable. Their empirical evidence shows that the weather variables are highly correlated with seasons, thus, it is hard to distinguish among them when trying to identify the weather variable/s that explains better stock returns. Finally, they show that seasonal effect is robust to different specifications, estimation techniques and addition of control variables.

[19] Yoon and Kang (2009) examine the relationship between stock returns and volatility and temperature, humidity, and cloud cover for the Korean stock market from 1990 to 2006. Furthermore, they examine whether the extent of a weather effect may have been weakened following the October 1997 financial crisis. The weather variables are converted into dummy variables and used in a linear regression model using the GJR-GARCH process in error terms. The interaction effects of the weather variables are also considered. They show that before the crisis, extremely low temperatures exerted a positive influence on returns, whereas extremely high humidity and heavy cloudiness exerted a negative effect on returns. However, after the 1997 financial crisis, evidence for a weather effect became insignificant. Finally, the conditional volatility of the Korean stock market tends to be higher when the news is unfavorable.

[20] Kelly and Meschke (2010) replicate and extend the sample of Kamstra et. al. (2003) from 9 countries (12 indices) to 36 countries (47 indices) and examine whether there are more pronounced stock market effects due to SAD in countries where the marginal trader is more likely to be afflicted by SAD. Specifically, they examine the link between SAD prevalence and the magnitude of seasonal returns in a more direct way. Based on their psychological literature, they find that the seasonality of the model predicted returns does not correspond to patterns of seasonal depression in the general population. Furthermore, their empirical evidence shows that the econometric specification of the SAD model mechanically induces the statistical significance for the SAD effect.

[21] The first type is related to the production of outputs given some inputs. Specifically, the production plan is assumed to be technically efficient if there is no way to produce more output with the same inputs or to produce the same output with fewer inputs (Favero and Papi, 1995). Therefore, if managers organize production so that the bank maximizes the amount of output produced with a given amount of inputs, then the bank is operating on its production frontier (Hughes and Mester, 2008). However, note that there are many underlying factors that could have an impact on the production frontier. To name a few we could mention: ownership (Taboada, 2011), non-traditional bank activities (Lozano-Vivas and Pasiouras, 2010) and market power (Delis and Tsionas 2009). On the other hand, cost efficiency measures the ability of a bank to minimize costs given the prices of inputs. By rephrasing, this type of efficiency measures how close or far the costs of a bank are from the costs of the best-practice bank, producing the same output under the same conditions. If costs of a bank are larger than the costs of the best-practice bank and the difference cannot be explained by any statistical noise, then the bank is characterized as cost inefficient (Mester, 1996). Finally, profit efficiency measures the ability of a bank to maximize profits, given the prices of inputs and outputs. In this case, it implies output maximization (cost minimization) at a given level of expenditures (output). Profit efficiency is a broader concept than

cost or productive efficiency, since its objective is both minimization of cost of the production of goods and services and maximization of revenues. In other words, it takes into consideration the effects of production not only on the cost side, but also on the revenue side and does not penalize high quality banks, since they compensate this cost 'inefficiency' by achieving higher revenues compared to their competitors (Maudos *et al.*, 2002). In addition, there have been some new developments in non-parametric measures of efficiency (Holod and Lewis, 2011)

[22] In order to check for potential multicollinearity correlations among the independent variables we calculated variance inflation factors (VIFs) for all control variables specified. Results are available upon request and indicate no multicollinearity problem.

[23] Panel VAR results for the main variables of our model, weather and bank loans efficiency are not of primer importance for this study. Results, however, are available under request.