Nowcasting Firms' Operating Activities from Satellite Data on Thermal Infrared Radiation

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Abstract

Practical real-world activities consume energy and emit thermal infrared radiation (TIR). On the basis of this physical fact, we develop a measure for directly gauging firms' operating activities. Specifically, we exploit satellite data to identify the TIR emitted by firms' factories during their production and to examine whether firms' TIR is informative about their future performance. Using a large dataset covering factories operated by publicly listed firms in China, we find that TIR declines following operational disruptions and strongly predicts firms' future sales growth and other dimensions of operating performance. TIR also forecasts future stock returns, particularly among opaque firms and those with limited investor accessibility. Interestingly, sophisticated investors do not appear to exploit TIR-based information, underscoring its value as a distinct and underutilized indicator of corporate fundamentals.

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1. Introduction

Industrial production underpins economic growth worldwide, powering job creation and technological innovation. Yet timely information on firm-level production remains scarce, as financial reporting cycles provide only infrequent snapshots of operations. In many advanced markets, such as the United States, analysts and policymakers benefit from multiple high-frequency indicators (e.g., non-farm payrolls, EIA crude oil inventories, and consumer confidence indices) that shed light on economic activity. By contrast, large manufacturing-driven economies such as China lack comprehensive, high-frequency metrics—beyond the Purchasing Managers' Index (PMI)—to monitor ongoing industrial operations. As a result, researchers and investors often have little choice but to rely on delayed periodic disclosures that may also be subject to managerial distortion (Chen & Yuan, 2004; Chen *et al.*, 2020).

In response to this challenge, a growing strand of literature has tapped "alternative data" sources, frequently capturing consumer behavior and preferences as proxies for corporate performance (Froot *et al.*, 2017; Huang, 2018; Zhu, 2019; Blankespoor *et al.*, 2022; Dichev & Qian, 2022; Li & Venkatachalam, 2022; Katona *et al.*, 2025). While these consumer-driven measures can help predict revenue or identify shifts in market demand, they focus primarily on selling activities—i.e., the *later* stages of the revenue generation process. Consequently, they illuminate only part of the picture. Direct measures of firms' operational or production activities—particularly in the *early*, manufacturing-intensive stages—are largely absent. This deficiency is particularly critical in a country like China, where thousands of publicly listed manufacturing firms occupy a central role in global supply chains but disclose limited real-time operational information.

In this study, we introduce a novel measure of firm-level operating activity by focusing on daily production dynamics, capturing the *early* stages of the revenue generation process. This approach provides a leading indicator of a firm's operational health and future financial performance, while also shedding light on the real economic consequences of managerial decisions—decisions often endogenously determined and difficult to observe using traditional data. Specifically, we draw on satellite data to track the thermal infrared radiation (TIR) emitted by firms' factories, establishing a broadly applicable and timely measure of production activity.

Our conceptual foundation rests on fundamental laws of thermodynamics (Thomson, 1853; Clausius, 1854), which dictate that all energy-consuming processes produce heat. According to the first law, energy is conserved and only transformed, while the second law asserts that these transformations are inevitably accompanied by energy loss in the form of heat due to entropy.[1] Thus, real-world processes such as combustion, mechanical operations, chemical reactions, and electrical usage inherently produce heat.

Industrially, firms consume significant energy during their production processes, generating heat detectable as TIR. Firms anticipating growth opportunities or increased demand are expected to expand their production and increase their operating activities, thereby emitting stronger TIR. Therefore, by monitoring changes in TIR intensity, we are able to observe and quantify real-time fluctuations in firm operations. Using high-resolution satellite imagery, we construct TIR for a large number of factories of Chinese publicly listed firms over a long period. We find that firms' TIR closely aligns with their operating activities and exhibits a significant relationship with their future financial performance and stock price movements.

TIR offers several unique advantages as a measure of firm-level operating activity. First, it captures the earliest phases of revenue generation—prior to revenue recognition in financial

[1] According to the second law of thermodynamics, the sum of entropies in all involved entities increases, meaning that overall orderliness declines. This necessitates the disposal of high-entropy waste (where orderliness is low) when materials and energy are transformed into products of low entropy (where orderliness is high).

statements—and therefore provides insights that the market has yet to price in. Since revenue is recognized only when it is earned and realizable, there is an inherent delay between production activity and its financial reporting. TIR offers a forward-looking view of firms' strategic initiatives, making it a valuable tool for forecasting and early trend detection.

Second, TIR enables real-time, granular tracking of firm-level activity across the universe of firms. Unlike prior satellite-based studies that focus on a small number of firms in a specific industry, such as major retailers (Katona *et al.*, 2025), or concentrate on broader macroeconomic indicators (Mukherjee *et al.*, 2021), TIR captures heat emissions from all economic activities, as all energy use generates thermal radiation under the laws of thermodynamics.

Third, TIR is timely and dynamic. Sensors onboard satellites like Landsat and MODIS capture high-resolution TIR data, rapidly processed and publicly available, enabling near-real-time monitoring of corporate activities. Huang *et al.* (2024) suggests that TIR data offer superior temporal predictions and reliable estimates even at geographically small scales.

These features make TIR a unique setting for measuring firm-level operations. To operationalize this, we identify the geographic boundaries and construction types of factories operated by publicly listed manufacturing firms in China. Leveraging satellite data from NASA's Landsat 8/9 and MODIS, we calculate factory-level TIR from 2014 to 2022. We then aggregate emissions across each firm's factories to construct firm-level TIR. Our final dataset comprises 61,346 year-quarter observations, covering 2,959 firms and 28,236 unique factories.

We begin by investigating whether TIR is responsive to firms' operating activities, using the staggered outbreaks of the COVID-19 pandemic in 2020 as exogenous shocks to corporate operations across different regions in China. The pandemic had a profound impact on manufacturing firms, disrupting production and straining supply chains (Okorie *et al.*, 2020).

Leveraging this natural experiment, we examine whether TIR declined among factories located in the affected areas.

Our analysis reveals that a one standard deviation increase in regional COVID-19 cases corresponds to a 32% reduction in the TIR of local factories. These results align with prior evidence on the operational disruptions caused by the pandemic (Okorie *et al.*, 2020). Additionally, detailed case studies of specific factories and industrial parks subject to government-mandated lockdowns or temporary closures further corroborate our findings.

Next, we assess whether TIR contains information not yet reflected in stock prices by analyzing its relationship with future sales and stock returns. We regress sales growth on changes in TIR while controlling for contemporary stock returns, firm and regional characteristics, and firm and time fixed effects. The results show that an increase in TIR significantly predicts higher sales growth in the subsequent quarter. Specifically, a one standard deviation increase in TIR is associated with a 5.3% rise in future sales growth for the median firm. This relationship remains robust across different satellite sources and methods of TIR construction.

Importantly, the predictive power of TIR is forward-looking. TIR changes in the current quarter forecast sales growth up to three quarters ahead but have no significant correlation with contemporaneous or past sales. Additionally, TIR is positively associated with key operational variables such as production costs, capital expenditures, labor employment, and profit margins—underscoring its value as an indicator of operating performance.

We further examine whether TIR predicts future stock returns. If TIR captures information not yet priced by the market, firms with higher TIR should earn higher subsequent returns. Fama–MacBeth regressions confirm this hypothesis: firms with higher TIR earn significantly higher returns in the following quarter, even after controlling for current stock returns. A hedge portfolio that buys firms in the highest TIR quintile and sells those in the lowest yields an annual abnormal return of 5.2%, with a cumulative abnormal return of 250% over the sample period—equivalent to an 11% annual return with compounding.

Interestingly, we do not observe a significant relationship between TIR and the trading behavior of sophisticated investors such as short sellers and institutional investors, including foreign participants. This suggests that the market has not yet fully incorporated TIR-based insights into pricing, reinforcing TIR's value as a distinct and underutilized information source.

Lastly, we find that TIR's predictive power for operating performance is especially strong in energy-efficient industries and among more productive firms. It is also positively associated with cumulative abnormal returns (CAR) around earnings announcements (EA), suggesting that markets react to information revealed by TIR but not captured by conventional data. This effect is even more pronounced for firms with lower transparency, fewer investor visits, and limited accessibility: highlighting TIR's value where traditional channels fall short.

Our study contributes to financial technology by introducing a direct, real-time, and scalable measure of firms' operating activities during production, a stage significantly preceding revenue recognition. Existing data sources in finance typically focus on selling activities (e.g., transactions, foot traffic, consumer ratings) (Huang, 2018; Blankespoor *et al.*, 2022; Dichev & Qian, 2022; Katona *et al.*, 2025) or rely on infrequent, aggregated disclosures that are prone to manipulation (Chen & Yuan, 2004; Chen *et al.*, 2020). In contrast, our TIR-based measure leverages thermal infrared radiation—a byproduct of energy use during production—to continuously track firms' operational intensity at the factory level. This addresses a critical gap in observing short-term fluctuations in manufacturing activity.

This innovation has important implications for both research and practice. First, it offers market participants, analysts, and policymakers with a new tool for gauging firm fundamentals outside traditional reporting windows. Second, it allows researchers to address core questions in corporate finance, such as how managers time equity or debt issues relative to operational expansions (Lee, 2021), how managerial actions align with or deviate from reported performance (Kothari *et al.*, 2009; Grieser *et al.*, 2021), and how firms adjust production in response to regulatory or environmental shocks (Grieser *et al.*, 2021). These questions have historically been challenging to answer due to data limitation.

Our work also extends the literature on satellite data in economics and finance. While prior studies use remote sensing to track macro trends (Burchfield *et al.*, 2006; Henderson *et al.*, 2012; Geddes *et al.*, 2016) or visible firm-level cues like parking lot traffic (Zhu, 2019; Katona *et al.*, 2025), our approach captures invisible thermal infrared emissions at the factory level. This enables granular, real-time monitoring of industrial operations, even in facilities hidden from conventional observation, offering a powerful tool for studying firm behavior beyond the reach of traditional data sources.

The remainder of the paper is structured as follows. Section 2 introduces the research background and hypotheses. Section 3 describes the data and methodology. Section 4 presents the empirical results, Section 5 offers additional analyses, and Section 6 concludes.

2. Research background and hypotheses

2.1. Related literature

Remote sensing satellite data have increasingly attracted the attention of researchers and financial institutions due to their ability to capture a broad range of human and economic activities. Initially, satellite data were widely utilized by scientists to detect natural disasters and climate change (Kudamatsu *et al.*, 2012; Guiteras *et al.*, 2015), quantify forest changes (Hansen *et al.*, 2013), estimate crop yields (Lobell, 2013), and analyze fishing conditions (Axbard, 2016). Satellite imagery has also been used to monitor human activities such as urban sprawl, housing construction, and environmental pollution. For example, Burchfield *et al.* (2006) employ satellite data to study land-use changes and urban development, Saiz (2010) investigates the impact of land constraints on housing prices, and Geddes *et al.* (2016) develop global measures of air pollution based on satellite-derived NO2 data.

Economists have extended satellite data applications to measure broader economic outputs. Henderson *et al.* (2012), using nighttime luminosity data from the Defense Meteorological Satellite Program–Operational Linescan System (DMSP-OLS), establish a connection between GDP growth and night light intensity across multiple countries. Chen and Nordhaus (2011) further demonstrate that night luminosity data significantly enhance GDP estimates, particularly in regions lacking robust statistical infrastructure.

Recently, financial economists have begun leveraging satellite imagery as a valuable source of alternative data to enhance insights into capital markets and firm-level performance. Katona *et al.* (2025) utilize satellite-derived data on store-level parking lot occupancy to predict performance metrics of major U.S. retailers, uncovering information not yet reflected in stock prices. Similar findings regarding the predictive power of parking lot data for firm fundamentals are reported by Zhu (2019) and Kang *et al.* (2021). Mukherjee *et al.* (2021) exploit satellite imagery to monitor crude oil inventory levels and forecast oil price movements.

Despite the broad applications of satellite data, most existing studies focus on macro-level analyses at regional or industrial scales, while firm-level analyses are relatively scarce and primarily limited to a few firms within the retail sector. In contrast, our paper explores the application of satellite data in a large and diverse sample of publicly listed firms, with data available at the factory level.[2]

In parallel, investors increasingly rely on alternative data sources beyond satellite imagery to gather granular insights about firm fundamentals. For instance, consumer-generated data, including customer ratings on Amazon (Huang, 2018), employee reviews on Glassdoor (Green *et al.*, 2019; Huang *et al.*, 2020), and investor comments on social media (Chen *et al.*, 2014; Tang, 2018), have been shown to significantly predict revenue, earnings surprises, and future stock prices. Even simple digital footprint data, such as mobile phone type or email providers, have predictive value for consumer payment behaviors and defaults (Berg *et al.*, 2020).

A common feature of existing alternative data applications in finance, including satellite imagery studies, is their focus primarily on later stages of firms' revenue generation processes, with emphasis on sales and consumer interactions. In contrast, our study contributes uniquely by focusing on the earlier stages of firms' revenue generation processes, employing TIR data from satellite imagery to *directly* measure firm-level production and operating activities.

2.2. Hypotheses

Our approach builds upon Georgescu-Roegen's bioeconomic theory, which views economic activity as a system transforming materials and energy with lower entropy into structured goods and services, simultaneously disposing of high-entropy byproducts. In this framework, the production process can be understood as infusing orderliness into products (Georgescu-Roegen, 1971).[3] However, according to the laws of thermodynamics, total energy must remain conserved, and entropy—reflecting disorder—invariably increases across all entities involved. Consequently,

[2] Some studies, such as those by Jean *et al.* (2016), Babenko *et al.* (2017), and Engstrom *et al.* (2017), use high-resolution imagery to identify economic indicators from landscape features. However, this approach requires complex deep learning algorithms because of the unstructured nature of the data. In contrast, TIR provides a more straightforward method, condensing these complex data into a single, uniform variable.

[3] Increased orderliness corresponds to lower entropy, while reduced order is associated with higher entropy.

economic activities inherently generate waste heat. Therefore, any anthropogenic activity necessarily results in heat emission, observable as TIR.[4]

Manufacturing firms consume significant amounts of energy during their production and operational processes, making them substantial sources of anthropogenic heat. Production lies at the core of the revenue generation process for manufacturing firms. As illustrated in Appendix 1, this process typically begins with product conceptualization and design. After finalizing designs, firms acquire property, purchase machinery, hire labor, and source necessary raw materials. Subsequently, these raw materials are converted into finished products through various manufacturing steps—such as machining and assembling—that require substantial energy and consequently produce significant amounts of TIR. These manufactured products are then stored, distributed, and ultimately sold to consumers, marking the conclusion of the revenue generation cycle. At this point, accountants recognize revenues and prepare financial reports disclosed on firms' EA days.[5]

When firms anticipate shifts in market conditions or adopt new operational strategies, they often adjust their production schedules and operational intensity, thereby altering the amount of TIR emitted. Thus, changes in the strength of TIR emissions can directly and promptly reflect changes in firms' fundamental conditions. Importantly, TIR emitted during these production activities is passively and continuously recorded by satellites, offering an objective and real-time measure of firm-level production activity.

Market participants seek and process information to form accurate assessments of firms' fundamental values. If investors have fully incorporated all relevant information (such as details

[4] According to Planck’s law, the spectral radiation of a black body depends solely on its surface temperature (Kogure & Leung, 2007). That is, the intensity of TIR is determined exclusively by the amount of heat generated.
[5] China introduced the Chinese Generally Accepted Accounting Principles (China GAAP) in 2007, the structure of which is similar to the Generally Accepted Accounting Principles of the United States (US GAAP) and International Financial Reporting Standards (IFRS).

from financial reports) into current stock prices, the informational content captured by TIR should already be reflected in stock performance. However, as illustrated in Appendix 1, there is a considerable gap between the timing of production, revenue recognition, and subsequent public disclosures. Furthermore, because TIR emissions are invisible to local observers or visitors, this information is unlikely to be readily accessible to investors. Given the intrinsic relationship between TIR emissions and firms' actual production activities, corporate-level TIR measurements likely contain information regarding firms' fundamentals that remains unanticipated by the market. We hypothesize that corporate TIR offers incremental predictive power regarding firms' future operating performance beyond that captured by current stock prices. This leads to our first hypothesis:

H1*: Corporate TIR is positively related to firms' future operating performance, controlling for current stock performance.*

Stock prices naturally fluctuate as new information becomes available. If TIR contains valuable information about firms' fundamentals that is not yet embedded in current stock prices, then TIR will significantly correlate with future stock price movements when this information is eventually realized by the market. This reasoning motivates our second hypothesis:

H2*: Corporate TIR is positively related to firms' future stock returns, controlling for current stock performance.*

3. Methodology

3.1. Satellite data

The satellite data for constructing our TIR measure come from NASA's Landsat 8 and 9 satellites, which offer high-accuracy thermal infrared sensing at a spatial resolution of 30 meters. Landsat 8, launched in February 2013, was later complemented by Landsat 9 in September 2021.[6] Their staggered 16-day imaging cycles allow the globe to be fully imaged every eight days since Landsat 9's launch.[7]

The United States Geological Survey (USGS) processes, archives, and distributes Landsat imagery. Initially available in near real-time (typically within 4–6 hours), images are later reprocessed and categorized into Tier 1 (highest-quality precision data) or Tier 2 (radiometrically equivalent but geometrically less precise, often due to cloud cover). We use both Tier 1 and Tier 2 images that are cloud-free within firms' factory areas and surrounding 5-km buffer zones.[8] These images are processed via Google Earth Engine (GEE), a platform widely utilized in satellite-data research (e.g., Burchfield *et al.*, 2006; Saiz, 2010; Hansen *et al.*, 2013).

Additionally, we consider MODIS satellite data, which offer a lower spatial resolution (1 km) but higher temporal frequency (daily imaging).[9] While our main analysis relies primarily on Landsat's higher-resolution imagery, we employ MODIS data for robustness tests and high-frequency observational examples.

3.2. Sample

Our sample comprises all manufacturing firms listed on China's two stock exchanges—the Shenzhen Stock Exchange (SZSE) and the Shanghai Stock Exchange (SHSE)—from the second quarter of 2014 (2014Q2) to the fourth quarter of 2022 (2022Q4) that are classified under the "C"

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[6] Although Landsat 9's instruments represent an updated version of those onboard Landsat 8, the underlying technology remains consistent, and both satellites maintain similar radiometric, geometric, spectral, and spatial characteristics.

[7] Unlike communication satellites, which operate in geostationary orbits, remote sensing satellites (such as Landsat and MODIS) utilize sun-synchronous orbits positioned much closer to Earth's surface (approximately 700 kilometers). These satellites do not rotate in sync with the Earth; instead, they orbit in a plane that maintains a fixed orientation relative to the sun. As Earth rotates eastward beneath them, these satellites progressively scan the surface westward, revisiting each location at the same local solar time each day. Consequently, remote sensing satellites can capture high-resolution images of Earth's entire surface with consistent illumination, facilitating accurate comparative analysis over time and across regions.

[8] Most images we use are Tier 1 images, with only 2.2% being Tier 2 images.

[9] When designing satellite sensors, there is typically a trade-off between spatial resolution and temporal frequency.

category in the 2012 China Securities Regulatory Commission (CSRC) Industry Classification. We focus on manufacturing companies because their operations, which are typically concentrated in factories, consume large amounts of energy and consequently emit substantial TIR. The starting point of 2014Q2 is chosen because Landsat 8 data have been available since 2013Q2, and data for change measurement are available from 2014Q2.

3.3. Measuring corporate TIR

The process for computing corporate TIR is outlined in Figure OA.1. We elaborate on the process as follows.

3.3.1. Identify the factory

A firm may operate multiple factories in different locations. To track the TIR of all factories of a firm, we first collect the addresses and ownership information of the firm's subsidiaries or plants (including the parent company or the plant located in the firm's headquarter) from the Controlled & Participated Company Database of Listed Companies (CPCD) on the Chinese Research Data Services (CNRDS) platform. Subsidiaries with at least 50% control by the listed firm are included.[10]

Next, using Google Maps/Earth, we manually pinpoint the exact location of each plant, noting the geographic outline and construction type. The geographic outline is determined by the quadrilateral most closely fitting the plant site. The coordinates of the four vertices and the geometric center of the quadrilateral are recorded. We use the satellite and street view modes to identify the construction type, which is categorized as "factory," "office building," or "a mix of factory and office building." Plants falling under "factory" or "a mix of factory and office

[10] According to the China Accounting Standards for Business Enterprises No. 33-Consolidated Financial Statements (2014), also known as CAS33 (2014), listed parent companies are required to include their controlled subsidiaries within the consolidation scope. This mandate is to ensure the preparation of consolidated financial statements that accurately reflect the operational results, financial status, and cash flows of the entire enterprise group, encompassing the parent company and all of its subsidiaries.

building" are defined as factories.[11]

Figure 1 provides an illustrative example using a Jianghuai Automobile plant located in Tongda, Hefei, Anhui Province. Image (a) of Panel A shows the geographic location of the plant, image (b) identifies it as a low-rise factory, and image (c) shows the factory's outline, with points A, B, C, and D marking the quadrilateral vertices.

[Insert Figure 1 about here]

3.3.2. Compute factory TIR

We use the algorithm used by Vanhellemont (2020a, 2020b) and Ermida *et al.* (2020) and input the coordinates of each factory into GEE to compute the TIR. The computed or observed factory TIR (*FR*) comprises both production-related TIR (adjusted TIR, *AR*) and TIR influenced by seasonal and regional factors (natural TIR). To focus on production-related TIR, we subtract the natural TIR from the observed TIR.

For this purpose, we estimate the TIR of bare lands (*BR*) within a 5 km radius around the factory, excluding the factory area itself (a buffer area). Bare lands, which are devoid of human inhabitants and production activities, are identified based on land cover categories from satellite data (Saiz, 2010). *BR* thus represents the natural TIR, unaffected by human activity. Because the TIR of the factory and buffer areas are observed in the same pass, they are subject to the same seasonal and regional factors and thereby share the same natural TIR. Consequently, the difference between FR and BR quantifies the production-related TIR. Specifically, the production-related TIR or adjusted TIR of a factory f at time t is defined as

$$AR_{f,t} = FR_{f,t} - BR_{f,t} \qquad (1)$$

Panel B of Figure 1 illustrates the TIR of the Jianghuai Automobile factory from a satellite

[11] Factories are often low-rise structures, being more expansive and utilitarian for manufacturing purposes. Office buildings, in contrast, tend to be high-rise, as they are more aesthetically designed structures geared toward administrative and professional work environments.

image taken on September 12, 2022 (the deeper the red, the stronger the TIR). Image (d) shows the TIR within a 5 km radius of the factory, image (e) depicts the TIR of the bare lands in the buffer area (*BR*), and image (f) represents the TIR of the factory area (*FR*). We observe that the TIR in the factory area and other industrial zones is significantly stronger than that in non-industrial areas. The adjusted TIR (*AR*) is calculated as the average TIR in image (f) minus the average TIR in image (e). We average all observations of *AR* within quarter q to obtain the factory's quarterly TIR, denoted as $AR_{f,q}$.[12]

3.3.3. Construct corporate TIR

The adjusted TIR at the corporate level is computed as either an equally weighted or investment-weighted average of $AR_{f,q}$ across all factories (*F*) of firm i in a given quarter:

$$AR_{i,q} = \sum_{f=1}^{F} W_f \cdot AR_{f,q} \qquad (2)$$

where W_f represents factory *f*'s initial investment as a proportion of the firm's total investment across all factories (investment-weighted) or is equal to 1/*F* (equally weighted). The equally weighted and investment-weighted versions of the firm's adjusted TIR are denoted as $ARe_{i,q}$ and $ARw_{i,q}$, respectively.

Finally, to better control for seasonal and regional factors, we compute the year-over-year change in adjusted TIR, denoted as $DAR_{i,q}$. Specifically, we define $DAR_{i,q}$ as the difference between the firm's adjusted TIR in quarter q and the adjusted TIR in the same quarter of the previous year (q-4), scaled by the absolute value of the previous year's adjusted TIR:

$$DAR_{i,q} = \frac{AR_{i,q} - AR_{i,q-4}}{|AR_{i,q-4}|} \qquad (3)$$

The two variations of the year-over-year change, corresponding to equally weighted and investment-weighted approaches, are denoted as $DARe_{i,q}$ and $DARw_{i,q}$, respectively. For a single

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[12] We construct the measure on a quarterly basis to align with firms' quarterly financial data.

factory, the year-over-year change in adjusted TIR is denoted as $DAR_{f,q}$.

3.4. Firm performance and control variables

We relate $DAR_{i,q}$ to firms' future operating and stock performance, controlling for the firms' stock prices and firm characteristics, as well as for regional characteristics in the current period.

We use sales growth, denoted as $SG_{i,q}$, to measure firms' operating performance for two basic reasons. First, sales stand at the final stage of firms' revenue generation process and represent the financially tangible outcome of firms' operating activities. Growth in sales is an indicator of market acceptance and value recognition of firms' operating outputs. Second, sales provide the most immediate accounting information available to gauge the financial consequences of operating outputs. Specifically, $SG_{i,q}$ is defined as a firm's total sales in quarter q minus its total sales in quarter $q–4$ (the same quarter of the previous year), scaled by its sales in quarter $q–4$.

In additional analyses, we study the link between $DAR_{i,q}$ and firms' other key operating activities in the revenue generation process. These include the cost of goods sold (COGS), which represents the direct costs of producing the goods sold, and capital expenditures and employment, which are one-time investments essential for starting production (see Appendix 1). Specifically, the variable $COGS_{i,q}$ represents a firm's total COGS in quarter q minus its total COGS in quarter q–4 (the same quarter of the previous year), scaled by its COGS in quarter q–4.

We measure firms' capital expenditures by creating $Capx_{i,q}$, which is the cash paid to acquire and construct fixed assets and other long-term assets divided by total assets in quarter q. We measure firms' employment using $Employment_{i,y}$, defined as the number of total employees in year y minus the total number of employees in year y–1, scaled by the total number of employees in year y–1.[13]

Finally, we explore the relationship between $DAR_{i,q}$ and firms' profit margins to close the loop and investigate whether firms' production expansion, as captured by $DAR_{i,q}$, is economically efficient. $OperatingMargin_{i,q}$ measures a firm's profit margin and is defined as the firm's operating income divided by its total sales in quarter q.

We measure firms' stock performance using $Ret_{i,q}$, which is a firm's stock return in quarter q. We also construct the stock's abnormal return $ARet_{i,q}$, which is the quarterly return minus the returns of the corresponding 5×5 market value and book-to-market (Size/BM) matched portfolio.

We control for firms' stock return in the current period, allowing to infer the performance predictability of $DAR_{i,q}$ based on information reflected in stock prices. We also control for observed time-varying firm characteristics ($FirmControl_{i,q}$), which are firm size (logarithm of market value, $Size_{i,q}$), financial leverage (total long-term debt/total assets, $Leverage_{i,q}$), profit status ($Loss_{i,q}$), firm valuation and investment opportunities (book value of equity/market value of equity, $BM_{i,q}$), asset tangibility (fixed assets/total assets, $Tangibility_{i,q}$), and the number of plants ($Plants_{i,q}$) (see Huang, 2018).

As TIR may be affected by climate conditions and regional development (Huang *et al.*, 2024), we further control for the regional characteristics ($RegionControl_{i,q}$) of factories' locations, which are the average temperature ($Temperature_{i,q}$), relative humidity ($Humidity_{i,q}$), precipitation ($Precipitation_{i,q}$), sunshine hours ($Sunshine_{i,q}$), GDP growth ($GDPGrowth_{i,q}$), and GDP per capita ($GDP/Capita_{i,q}$) across a firm's factory location cities. The definitions and data sources of the variables used in this study are provided in Table OA.1.

[13] We use annual employment growth because the data on the number of employees are only available on an annual basis.

3.5. Summary statistics

Our final sample comprises 61,346 year-quarter observations, involving 2,959 unique publicly listed firms and 28,236 unique factories. To validate our measures, we begin with a factory-level analysis that examines how these measures respond to COVID-19 outbreaks. We then conduct a firm-level analysis to assess the relationship between our measures and future firm performance.

Table 1 provides summary statistics for the variables used in this study. Panel A presents statistics for the factory-level analysis, showing an average $AR_{f,q}$ of 3.23 Kelvin.[14] This indicates that, on average, the difference in TIR between factory areas and their surrounding buffer zones is 3.23 Kelvin. Panel B presents statistics for the firm-level analysis. The average year-over-year change in the equally weighted adjusted TIR ($DARe_{i,q}$) and the investment-weighted adjusted TIR ($DARw_{i,q}$) are both approximately 0.32. The standard deviations for $DARe_{i,q}$ and $DARw_{i,q}$ are 1.85 and 1.87, respectively. The mean and median sales growth in the subsequent quarter ($SG_{i,q+1}$) are 18.75% and 9.82%, respectively, with a standard deviation of 53.43%.

[Insert Table 1 about here]

4. Proof-of-the-pudding

4.1. TIR and operational disruptions

Before examining the economic significance of corporate TIR, we first validate our measure by analyzing how it responds to operational disruptions. To achieve this, we use the COVID-19 outbreaks as shocks to corporate activities and examine whether the TIR of the affected factories decline in response. The COVID-19 pandemic, first identified in Wuhan, China, in December 2019, spread rapidly nationwide and subsequently worldwide. This pandemic significantly

[14] This dataset covers the period from the first quarter of 2019 to the second quarter of 2020, encompassing 18,423 unique factories.

impacted manufacturing firms' operating performance through production disruptions, labor shortages, and supply chain challenges (Okorie *et al.*, 2020). If our TIR measure accurately tracks firms' production and operating activities, it should show a decline in response to these shocks.

4.1.1. Difference-in-difference regression

To precisely capture how TIR responds to the staggered COVID-19 outbreaks in different regions of China, we perform our analysis at the factory level. Specifically, we adopt a difference-in-differences (DID) approach, employing a factory-quarter panel dataset spanning from the first quarter of 2019 (2019Q1) to the second quarter of 2020 (2020Q2). The DID regression model is specified as follows:

$$TIR_{f,q} = \alpha_0 + \alpha_1\, COVID19_{f,q} + \alpha_2\, Ret_{i,q} + FirmControl_{i,q} + RegionControl_{f,q} + \boldsymbol{F_f} + \boldsymbol{Q_q} + \varepsilon_{f,q}, \quad (4)$$

where the dependent variable $TIR_{f,q}$ represents either the adjusted TIR level ($AR_{f,q}$) or its year-over-year change ($DAR_{f,q}$) for factory f of firm i in quarter q. The key explanatory variable, $COVID19_{f,q}$, is defined as the natural logarithm of one plus the number of new COVID-19 infections reported in the city where factory f is located during quarter q.

We control for contemporaneous stock returns ($Ret_{f,q}$) and various firm characteristics ($FirmControl_{f,q}$) of factory f's listed firm i. We also control for the regional characteristics ($RegionControl_{f,q}$) of factory f's location city. We further include *factory fixed effects* ($\boldsymbol{F_f}$) and *year-quarter fixed effects* ($\boldsymbol{Q_q}$). α_1 is therefore the DID estimate, which represents the change in a factory's TIR when the infection count in its location city is high relative to the factory's TIR when the infection count is low or compared with the TIR of factories in other cities with low infection numbers. The results are reported in Table 2.

We find negative and statistically significant coefficients on $COVID19_{f,q}$ in the regression models analyzing both $AR_{f,q}$ (Columns 1-2) and $DAR_{f,q}$ (Columns 3-4). This indicates that the TIR emitted by factories decreases as the local severity of the COVID-19 pandemic increases.

Specifically, Column (1), which excludes control variables, yields a COVID-19 coefficient of –0.078, statistically significant at the 5% level. When firm-level and regional controls are included in Column (2), this coefficient slightly strengthens to –0.086 and becomes statistically significant at the 1% level. The economic significance of this result is substantial; a one-standard-deviation increase in local COVID-19 infection intensity corresponds to a decrease in adjusted TIR by approximately 0.17 Kelvin (1.88 × 0.09).

Column (3) reports results using $DAR_{f,q}$ without additional controls, producing a negative COVID-19 coefficient of –0.054, significant at the 1% level. This finding suggests that factories facing more severe local outbreaks also experience relative reductions in thermal emissions compared to prior periods. After including the complete set of controls in Column (4), the coefficient remains robust at –0.057, significant at the 5% level. The economic implication remains pronounced: a one-standard-deviation increase in COVID-19 infections is associated with an approximately 0.11-unit decline in $DAR_{f,q}$ (1.88 × 0.06), equivalent to a 32.43% reduction relative to the sample mean of 0.35. Collectively, these results confirm that TIR effectively and sensitively reflects the real-time operational disruptions experienced by factories during the COVID-19 pandemic.

[Insert Table 2 about here]

4.1.2. Case evidence

To further assess the validity of our measurement, we present detailed case studies of specific factories that experienced government-mandated lockdowns or temporary operational suspensions with clearly defined dates. We analyze their daily observations of thermal emissions using MODIS satellite data.[15]

Figure 2 presents two representative cases.[16] Panel A shows the case of Angel Yeast (Ili) Co., Ltd., located in Yining City, Xinjiang, which experienced a government-mandated shutdown due to a COVID-19 outbreak from October 3 to November 17, 2021. Panel A.1 provides aerial imagery highlighting factory boundaries, while Panel A.2 plots the adjusted daily TIR data obtained from MODIS. Immediately following the shutdown, the factory's adjusted TIR declined sharply by approximately 2.76 Kelvin, representing an 88.7% reduction compared to pre-shutdown levels. Similarly, Panel B depicts Shijiazhuang Huigu Enterprise Management Co., Ltd., located in Shijiazhuang, Hebei Province, which underwent a temporary closure between November 2 and November 15, 2021. Consistent with the precise shutdown period, the factory's adjusted TIR dropped notably by 1.43 Kelvin (81.4%), highlighting a clear alignment between observed emissions and the actual operational halt.

[Insert Figure 2 about here]

Figure 3 extends this analysis to a larger-scale industrial zone—Yinan Industrial Park in Yili, Xinjiang—which underwent a government-mandated operational suspension from August 3 to November 16, 2022. Due to its expansive footprint, this case is particularly amenable to MODIS's 1-km resolution imagery. Panel A provides the park's geographic boundaries and aerial imagery.

[Insert Figure 3 about here]

Panels B and C visually contrast TIR before and after the operational shutdown, offering

[15] MODIS provides daily imagery but at a lower spatial resolution of 1 km, whereas Landsat 8/9 offers higher-resolution imagery at 30 meters, though only every eight days.

[16] One limitation of high-frequency satellite data from MODIS is that cloud cover can lead to missing daily observations. Consequently, MODIS provides fewer data points for factories located in regions frequently affected by cloud cover, such as southern and eastern China. To minimize this concern, we specifically selected cases from northwestern and northern China, regions typically experiencing fewer cloudy days.

striking evidence of TIR reduction. Panel B displays raw thermal infrared heatmaps, illustrating substantial differences between pre- and post-shutdown periods. Panel C further refines this visualization by presenting adjusted TIR maps, which subtract the TIR from surrounding bare lands within a 5-kilometer radius to isolate anthropogenic heat emissions from operational activities. For an even clearer demonstration of temporal patterns, animated daily adjusted TIR images are provided online, effectively showcasing day-by-day operational changes.

Panel D plots daily adjusted TIR values around the shutdown event, revealing a sharp decrease of approximately 1.74 Kelvin, or a 41.9% reduction relative to pre-shutdown levels. This distinct and immediate reduction precisely aligns with the timing of the mandated shutdown, underscoring the sensitivity and accuracy of our measure in detecting rapid operational disruptions.

To enhance the robustness and generalizability of these observations, we conduct an aggregated analysis of factory shutdown incidents across our entire sample period. Initially, we identify 143 incidents potentially relevant to operational disruptions, including shutdowns triggered by localized COVID-19 outbreaks, unexpected supply chain disruptions, and regulatory interventions. We exclude incidents lacking sufficient TIR data, those arising from events (such as fires, storms, floods, or relocations) that themselves could affect the TIR measurements, cases with unclear shutdown dates, or incidents affecting only partial production lines or specific products with limited operational impact. This filtering process yields a final set of 56 valid shutdown events, with detailed criteria summarized in Panel A of Figure 4.

[Insert Figure 4 about here]

Panel B aggregates the daily TIR observations across these 56 factory shutdown incidents. The results reveal a substantial and statistically significant decline in adjusted TIR coinciding precisely with the shutdown dates. On average, adjusted TIR decreases by approximately 0.26 Kelvin, equivalent to a 24% reduction relative to pre-shutdown activity levels.

These findings highlight the practical effectiveness of TIR data in capturing corporate activity and its dynamics in response to high-frequency disruptions in industrial operations.

4.2. TIR and firms' operating performance and returns

Having established that TIR effectively captures firms' operating activities, we now turn to testing our hypotheses. Specifically, we examine the economic implications of TIR by analyzing how variations in corporate TIR are related to firms' future fundamental performance and stock returns.

4.2.1. TIR and operating performance

A. Sales growth

To test our first hypothesis, we run the following model:

$$y_{i,q+1} = \beta_0 + \beta_1\, DAR_{i,q} + \beta_2\, Ret_{i,q} + FirmControl_{i,q} + RegionControl_{i,q} + \boldsymbol{I_i} + \boldsymbol{Q_q} + \varepsilon_{i,q}, \quad (5)$$

where the dependent variable $y_{i,q+1}$ is the year-over-year sales growth ($SG_{i,q+1}$) of firm i in quarter $q+1$. $DAR_{i,q}$ is the year-over-year change in the adjusted TIR, either the equally weighted TIR $DARe_{i,q}$ or the investment-weighted TIR $DARw_{i,q}$. $Ret_{i,q}$ is current stock performance, the buy-and-hold stock return in quarter q. We control for both time-varying firm characteristics ($FirmControl_{i,q}$) and average regional characteristics across firms' factory locations ($RegionControl_{i,q}$). We include *firm fixed effects* ($\boldsymbol{I_i}$) to control for firm-specific, time-invariant factors and *year-quarter fixed effects* ($\boldsymbol{Q_q}$) to control for aggregate, time-varying factors. The coefficients of the model are estimated with standard errors clustered at both the firm and year-quarter level.

The estimates are reported in Table 3. We find that firms' TIR is positively and significantly related to their sales growth in the subsequent quarter. Since the estimated coefficients on *DAR* remain consistent regardless of control inclusion, we focus primarily on the specifications with full controls (Columns 2 and 4). Specifically, as shown in Column (2), the coefficient on the equally weighted TIR, $DARe_{i,q}$, is 0.31, which is significant at the 1% level. This suggests that a one standard deviation increase in $DARe_{i,q}$ is associated with a 0.57% (1.85×0.31) increase in $SG_{i,q+1}$. For a firm with a median level of $SG_{i,q+1}$, this translates to a 5.80% increase. In Column (4), where the investment-weighted TIR, $DARw_{i,q}$, is used, the coefficient is 0.28, which is significant at the 5% level. This indicates that a one standard deviation increase in $DARw_{i,q}$ corresponds to a 0.52% (1.87×0.28) increase in $SG_{i,q+1}$, equating to a 5.33% increase for a median firm.

Notably, we observe that stock returns ($Ret_{i,q}$) are positively and significantly related to subsequent-quarter sales growth, which implies that current stock performance is indicative of firms' future performance. This, in combination with our findings on TIR, suggests that TIR contains information about future firm performance not yet reflected in current stock prices.

[Insert Table 3 about here]

To visualize these patterns, Figure OA.2 plots the quarterly average of abnormal $DARw_{i,q}$ and $SG_{i,q+1}$, showing that the two series closely co-move across time. Both variables declined sharply during the early 2020 COVID-19 outbreak and rebounded when production and economic activity resumed. Figure OA.3 displays the cross-sectional relationship between industry-level averages of abnormal TIR and sales growth, revealing a clear positive association. Industries such as transportation equipment, foods, and automobiles exhibit strong simultaneous increases in both metrics, while sectors like beverages and chemicals show contraction.

To further explore the dynamics of the relationship between TIR and firm fundamentals, we extend our analysis to assess whether TIR in the current quarter predicts sales growth over longer horizons. Specifically, we replace the dependent variable in Model (5) with sales growth in different quarters relative to the TIR measurement ($SG_{i,q+n}$, where n = -1 to 6). The estimates with full controls are reported in Table 4, while those without controls are presented in Table OA.2. The results show that both TIR measures significantly predict sales growth up to three quarters ahead (n = *1*, *2*, *3*), but lose predictive power beyond that horizon. In contrast, TIR is not significantly associated with contemporaneous or lagged sales growth (n = 0 or -1), consistent with the view that production activity—as captured by TIR—precedes revenue recognition. These findings reinforce the interpretation of TIR as a forward-looking indicator of firms' operating performance.

[Insert Table 4 about here]

Our findings are robust to a range of alternative specifications, as detailed in Table OA.3. We find consistent predictive power of TIR when using different satellite sources (Landsat 8 only, Tier 1 only, MODIS), varying weighting schemes, and excluding the COVID-19 period. Moreover, TIR derived from non-headquarters factories drives the results, while TIR from office buildings shows no predictive power, reinforcing the validity of our production-based measure. These robustness checks confirm that the observed relationship between TIR and future sales growth is not sensitive to measurement choices or sample restrictions.

B. Other operating activities

We further explore whether corporate TIR is associated with firms' operating activities during key stages of their revenue generation process (see Appendix 1). While existing databases do not provide real-time data on firms' operations, observing a relationship between TIR and subsequent disclosures of operating activities helps validate the intrinsic link between TIR and operational fundamentals. First, because TIR tracks a firm's production activities, we investigate its relationship to the firm's product costs, namely COGS ($COGS_{i,q}$).

Second, we examine whether TIR is related to firms' capital expenditures ($Capx_{i,q}$) and employment ($Employment_{i,y}$). COGS reflects the direct production costs associated with the products sold. However, it does not include one-time investments in fixed assets and labor, which are essential for initiating manufacturing and production.

Third, if a firm's production expansion, as indicated by TIR, responds efficiently to the increase in demand, the rise in sales should surpass the increase in production costs and other operating costs, resulting in a higher profit margin ($OperatingMargin_{i,q}$).

We re-estimate Model (5) by replacing the dependent variable with these four variables. For the quarterly variables—*COGS*, *Capx*, and *OperatingMargin*—we use their lead values to capture future operating outcomes relative to current TIR ($COGS_{i,q+1}$, $Capx_{i,q+1}$, and $OperatingMargin_{i,q+1}$). However, for *Employment*, we use the variable measured in the same year rather than in lead form ($Employment_{i,y}$). This is because employment data are available only on an annual basis, which limits the temporal granularity of the analysis. As such, using contemporaneous annual data allows us to approximate the relationship between changes in TIR and employment dynamics over the same calendar year.

The results, presented in Table 5, provide strong support for the link between corporate TIR and firms' other operating activities. Panel A reports the estimates for $COGS_{i,q+1}$. The coefficients on both $DARe_{i,q}$ and $DARw_{i,q}$ are positive and statistically significant, indicating that firms with higher TIR tend to incur greater production costs in subsequent quarters. This finding reinforces the idea that corporate TIR effectively captures production activity. Moreover, these results are consistent with the sales growth findings in Table 3, supporting the accounting matching principle, which states that expenses are recognized in the same period as the revenues they help generate. For instance, as shown in Column (4), a one standard deviation increase in $DARw_{i,q}$ is associated with a 0.39% (1.87 × 0.21) increase in $COGS_{i,q+1}$. This increase is smaller than the corresponding 0.52% rise in $SG_{i,q+1}$, suggesting that sales tend to outpace production costs in response to expanded operations, as reflected by TIR.

Panel B presents the results for $Capx_{i,q+1}$. We find that both TIR measures—$DARe_{i,q}$ and $DARw_{i,q}$—are positively and significantly related to capital expenditures. This suggests that firms with increasing TIR are more likely to invest in long-term assets, such as property, plant, and equipment, consistent with an expansion in production capacity.

Panel C shows the estimates for annual employment growth ($Employment_{i,y}$). The coefficients on both TIR measures remain positive and significant at the 5% level, indicating that firms with rising TIR are also more likely to hire additional workers. This further supports the interpretation of TIR as a proxy for real operating expansion.

Panel D reports the estimates for $OperatingMargin_{i,q+1}$. Both $DARe_{i,q}$ and $DARw_{i,q}$ are positively and significantly associated with profit margins, suggesting that production expansion leads not only to higher output but also to greater efficiency. Specifically, using Column (4) for instance, a one standard deviation increase in $DARw_{i,q}$ is associated with a 0.11% (1.87 × 0.06) rise in $OperatingMargin_{i,q+1}$, which translates to a 1.6% increase for a firm with the median operating margin. These results are consistent with the presence of economies of scale, where higher production volumes reduce per-unit operating costs, thereby improving profitability.

Taken together, the evidence indicates that corporate TIR is a strong and consistent predictor of firms' broader operating activities and performance.

[Insert Table 5 about here]

4.2.2. TIR and stock returns

Our evidence suggests that TIR is related to firms' future operating performance. If market participants are unaware of this indicator or do not have access to the firm performance reflected in TIR, it should correlate with future stock price movements when this information becomes public. We test our second hypothesis regarding whether TIR can inform investors about firms' future stock returns using Fama–MacBeth regression and portfolio analysis.

A. *Fama–MacBeth regression*

We conduct a Fama–MacBeth (1973) regression, which is specified as follows:

$$Return_{i,q+1} = \gamma_0 + \gamma_1\, DAR_{i,q} + \gamma_2\, Ret_{i,q} + FirmControl_{i,q} + RegionControl_{i,q} + \boldsymbol{IND_i} + \varepsilon_{i,q}, \quad (6)$$

where $Return_{i,q+1}$ represents firm i's raw stock return ($Ret_{i,q+1}$) and abnormal returns ($ARet_{i,q+1}$) in quarter q+1. Importantly, we control for the stock return in the current quarter $Ret_{i,q}$, allowing to infer the return predictability of $DAR_{i,q}$ based on information reflected in the current stock prices. $\boldsymbol{IND_i}$ is industry fixed effects. We run the model across all firms for every quarter and then average the coefficients on $DAR_{i,q}$ over time to determine the final estimate of γ_1. The standard deviation of the coefficients is adjusted using the Newey–West estimator.

The results are reported in Table 6. Panel A shows the results when the dependent variable is $Ret_{i,q+1}$. We observe that the coefficients on $DARe_{i,q}$ and $DARw_{i,q}$ are positive and statistically significant at the 5% level, both with and without control variables. This indicates that firms with higher TIR in a given quarter tend to earn higher stock returns in the following quarter. The economic magnitude is also meaningful: for example, in the full model with controls, a one standard deviation increase in $DARw_{i,q}$ is associated with a 0.19% (1.87 × 0.10) increase in $Ret_{i,q+1}$, representing roughly a 5% improvement over the sample mean.

Panel B presents the results when the dependent variable is $ARet_{i,q+1}$. We find a similar pattern. The coefficients on both $DARe_{i,q}$ and $DARw_{i,q}$ are positive and significant at the 1% level when full controls are included. A one standard deviation increase in $DARw_{i,q}$ is associated with a 0.21% (1.87 × 0.11) increase in $ARet_{i,q+1}$, an increase of approximately 7% from the mean.

Additionally, we note that the coefficient on the stock return in the current quarter ($Ret_{i,q}$) is negatively related to the return in the next quarter, which suggests that high stock returns tend to reverse in future periods (Benou & Richie, 2003).

[Insert Table 6 about here]

B. Portfolio analysis

Next, we form portfolios based on the sorted $DAR_{i,q}$ and test whether these portfolios earn abnormal returns. Specifically, for each month from 2014Q2 to 2022Q4, we sort our sample stocks into quintiles based on $DAR_{i,q}$, which is constructed over the past three months or quarter. We create a zero-cost hedge portfolio that buys stocks in the top quintile (P5) and sells stocks in the bottom quintile (P1) of $DAR_{i,q}$. The portfolios are rebalanced monthly. We then calculate the portfolios' excess returns, which are the raw returns minus the risk-free rate, and compute the alpha by regressing the portfolios' returns on the Fama–French three factors (FF3) (Fama & French, 1993), the Fama–French–Carhart four factors (Carhart4) (Carhart, 1997), and the Fama–French five factors (FF5) (Fama & French, 2015). The estimated constant from this regression is the alpha, or average monthly abnormal return, of each portfolio. The results are presented in Table 7.

Panel A, which reports the results based on the equally weighted TIR $DARe_{i,q}$, shows that portfolio returns increase monotonically with $DARe_{i,q}$. The excess returns, as shown in Column (1), range from 1.96% in P1 to 2.37% in P5. The hedge portfolio's excess return is 0.40%, which is significant at the 5% level. This is equivalent to an annualized excess return of 4.80%. Alphas based on the FF3, Carhart4, and FF5 models are reported in Columns (2)–(4) and show similar patterns. For instance, under the FF5 model, the alpha for P1 is 1.09%, increasing to 1.55% for P5. The hedge portfolio's alpha is 0.46%, equivalent to 5.52% per year.

Panel B reports the results based on the investment-weighted TIR $DARw_{i,q}$, which show similar trends. Both the excess returns and alphas increase monotonically with $DARw_{i,q}$. The hedge portfolio's excess return is 0.43% (annualized = 5.16%), and the alpha under the FF5 model is 0.45% (annualized = 5.40%).

To visually corroborate these findings, we plot the buy-and-hold cumulative excess returns of the hedge portfolio constructed based on $DARw_{i,q}$ throughout our sample period in Figure OA.4. The return increases steadily, reaching as high as 250% by the end of 2022. This equates to an annualized return of 11% with compounding.

Overall, the results suggest that an investment strategy based on corporate TIR can yield significant abnormal returns. This supports our hypothesis that corporate TIR provides valuable insights into firms' future stock performance.

[Insert Table 7 about here]

4.2.3. TIR and sophisticated investors

Processing satellite data requires sophisticated skills. To complete our analysis, we examine whether TIR is related to the trading activities of sophisticated investors, such as short sellers and institutional investors (like hedge funds). First, sophisticated investors may have access to satellite data and thus directly trade based on TIR information. Second, they may access insider information or other data related to TIR by having private meetings with management, or they may possess advanced techniques for analyzing firms' public disclosures (Engelberg *et al.*, 2012;

Solomon & Soltes, 2015; Bushee *et al.*, 2018) and thereby trade on TIR information indirectly. However, if sophisticated investors lack access to satellite data or the information contained in TIR is unique and beyond their exploration, there would be no connection between their trading activities and TIR.

To conduct the test, we correlate $DAR_{i,q}$ with contemporary changes in net short interest ($DSHO_{i,q}$) and changes in institutional investors' positions ($DIO_{i,q}$). The CSMAR database provides the number of short interests opened and closed daily for firms that are available for short selling in China. For this subset of firms, we average the daily net short position (i.e., (short interest opened – short interest closed) / total trading volume) within a quarter to obtain the quarterly net short position ($SHO_{i,q}$) (Engelberg *et al.*, 2012). $DSHO_{i,q}$ is the net short position in quarter q ($SHO_{i,q}$) minus the net short position in quarter $q–4$ ($SHO_{i,q–4}$). $DIO_{i,q}$ is the percentage of shares held by institutional investors in quarter q minus the percentage in quarter q–4 (Huang, 2018). We re-estimate Model (5), replacing the dependent variable with these two variables. The results are reported in Table 8.

Panel A presents the results for $DSHO_{i,q}$ based on the sample of firms that are allowed to short sell. We find that the coefficients on $DARe_{i,q}$ and $DARw_{i,q}$ are negative and statistically non-significant, implying that short sellers appear neither to access TIR satellite data nor to obtain information contained in TIR. Interestingly, $DSHO_{i,q}$ is positively related to contemporary stock returns ($Ret_{i,q}$), which suggests that short sellers increase their positions when stock prices rise.

Panel B presents the results for $DIO_{i,q}$ based on the full sample. We observe that the equally weighted TIR $DARe_{i,q}$ is weakly and positively related to $DIO_{i,q}$. The coefficient on the investment-weighted $DARw_{i,q}$ is positive but not significant at conventional statistical levels.

[Insert Table 8 about here]

We also explore whether foreign investors are more likely to use satellite data to monitor firm performance. Due to geographic and language barriers, foreign investors face higher information acquisition costs via traditional channels such as site visits (Cheng *et al.*, 2016). As a result, they may have a greater incentive to utilize satellite imagery to monitor their investment overseas.

To evaluate this hypothesis, we conduct two additional tests. First, we measure foreign ownership using the shareholding data of qualified foreign institutional investors (QFII) in China (Jiang *et al.*, 2020).[17] We compute the year-over-year change in QFII holdings ($DQFII_{i,q}$) and relate it to both $DARe_{i,q}$ and $DARw_{i,q}$. The results, reported in Table OA.4, show no statistically significant relationship between QFII ownership changes and TIR, suggesting that foreign institutional investors are not actively using TIR data in their decision-making.

Second, we examine whether TIR is related to the A–B share price difference ($A\text{-}B\ PriceDif_{i,q}$) (Darrat *et al.*, 2010).[18] Prior research suggests that B-share discounts arise because domestic investors tend to overvalue A-shares due to information asymmetries. Specifically, A-share investors are less informed about firms' fundamentals compared to B-share investors (Yang, 2003). Consequently, if foreign investors were utilizing TIR data to gain an informational advantage, we would expect a significant correlation between TIR and the A–B share price differential. However, as reported in Table OA.5, we find no such relationship, further suggesting that foreign investors are not engaging with TIR satellite data.

Collectively, these findings provide no clear evidence that sophisticated investors—whether domestic or foreign—are actively incorporating TIR information into their trading strategies. This underscores the uniqueness of our TIR measure as a source of firm-level information that

[17] Qualified foreign institutional investors (QFIIs) can buy A-shares of Chinese stocks since 2003.
[18] In China, A shares are stocks traded in RMB on the two main exchanges, primarily for domestic investors, while B shares are traded in foreign currencies (USD in Shanghai, HKD in Shenzhen) and were originally for foreign investors.

remains largely untapped by the market.

5. Additional analysis

5.1. The effect of energy efficiency and productivity

Our previous analysis indicates that corporate TIR is related to firms' operating performance. In this sub-section, we conduct additional analyses to understand this relationship in depth.

The sensitivity of TIR in response to firm performance varies across industries, as demonstrated in Figure OA.3. Some firms may be more energy-efficient or possess superior technologies for converting energy into useful work and outputs (i.e., higher productivity), enabling them to generate more sales with less energy. This leads to a stronger relationship between $DAR_{i,q}$ and $SG_{i,q+1}$. To test this, we investigate how the relationship between $DAR_{i,q}$ and $SG_{i,q+1}$ varies with firms' energy efficiency and productivity.

We measure energy efficiency at the industry level, defined as the total sales of the industry to which a firm belongs, scaled by the total energy consumption of the industry in a quarter ($Energy_{i,q}$). $Energy_{i,q}$ is assigned a value of 1 if the energy efficiency of a firm's industry ranks in the top decile, and 0 otherwise. We gauge firms' technology or productivity using TFP, which is computed based on the Levinsohn and Petrin (2003) (LP) approach ($TFP_{i,q}$). $TFP_{i,q}$ is assigned a value of 1 if the TFP computed for a firm ranks in the top decile of the sample, and 0 otherwise. Additionally, in China, firms controlled by the government (SOEs) are widely believed to be less efficient and to have lower productivity than privately owned firms (non-SOEs) (Sun & Tong, 2003; Jiang & Kim, 2020). Hence, we use state ownership ($SOE_{i,q}$) as a proxy for productivity and examine its impact on the relationship between $DAR_{i,q}$ and $SG_{i,q+1}$. $SOE_{i,q}$ takes a value of 1 if a firm is ultimately owned by the state government in a quarter, and 0 otherwise. We incorporate the interactions between $DAR_{i,q}$ and these three variables into Model (5), focusing on the investment-weighted TIR ($DARw_{i,q}$) to save space.

The results are reported in Table 9. The coefficients on $DARw_{i,q} \times Energy_{i,q}$ are positive, significant at the 10% level. For instance, in Column (2), the coefficient on the interaction term is 1.04, and the coefficient on $DARw_{i,q}$ is 0.17. This implies that a one standard deviation increase in $DARw_{i,q}$ is associated with a 2.26% (1.87 × (0.17 + 1.04)) increase in $SG_{i,q+1}$ in firms with high energy efficiency ($Energy_{i,q}$ = 1), compared with only 0.32% (1.87 × 0.17) in firms with low energy efficiency ($Energy_{i,q}$ = 0).

Columns (3) and (4) present the results regarding the impact of TFP. The coefficient on $TFP_{i,q}$ is positive and significant, indicating that firms with high TFP have high sales growth. As shown in column (4), the coefficients on $DARw_{i,q}$ and $DARw_{i,q} \times TFP_{i,q}$ are 0.20 and 0.98, respectively. This indicates that a one standard deviation increase in $DARw_{i,q}$ is associated with a 2.21% (1.87 × (0.20 + 0.98)) increase in $SG_{i,q+1}$ in firms with high TPF ($TFP_{i,q}$ = 1), while it is only 0.37% (1.87 × 0.20) in firms with low TFP ($TFP_{i,q}$ = 0).

The effect of state ownership is detailed in Columns (5) and (6). Consistent with SOEs being less efficient, the coefficient on $SOE_{i,q}$ is negative and significant. The coefficient on $DARw_{i,q}$ in Column (6) is 0.42, which is significant at the 1% level, and the coefficient $DARw_{i,q} \times SOE_{i,q}$ is –0.50, which is significant at the 10% level. Hence, a one standard deviation increase in $DARw_{i,q}$ is associated with a 0.79% (1.87 × 0.42) increase in $SG_{i,q+1}$ for non-SOEs, but only a negligible –0.15% (1.87 × (0.42 – 0.50)) for SOEs.

[Insert Table 9 about here]

5.2. TIR and earnings news

To further substantiate the stock return predictability of TIR, we examine whether investors are aware of the information contained in TIR prior to EAs. If investors observe such information or other indicators related to TIR before EAs, they are likely to incorporate it into their decision-making and consequently will not be surprised when firms' earnings are publicly released. Conversely, if investors do not realize the information contained in TIR, they are likely to be surprised by EAs and to make adjustments in their decisions, leading to a positive relationship between the market reaction and TIR.

We measure the market reaction using the three-day CAR around firms' quarterly EAs, $CAR(-1,1)_{i,q+1}$, which is the three-day CAR computed based on the capital asset pricing model (CAPM) around the EA day (day 0) of firm i in quarter $q+1$. We re-estimate Model (5) by replacing the dependent variable with $CAR(-1,1)_{i,q+1}$. The results are reported in Table OA.6.

We find that the coefficients on both $DARe_{i,q}$ and $DARw_{i,q}$ are positive and significant, indicating that investors are not fully aware of the information contained in TIR and make trading adjustments at EAs in a direction in line with TIR.[19] Specifically, using the last column for instance, the coefficient on $DARw_{i,q}$ is 0.03. This means that a one standard deviation increase in $DARw_{i,q}$ is associated with a 0.06% (1.87 × 0.03) increase in $CAR(-1,1)_{i,q+1}$.

Figure OA.5 plots the CAR around EA for stocks in the top and bottom quintiles of $DARw_{i,q}$, labeled "High" and "Low," respectively. The "High" portfolio shows an uptick in returns, while the "Low" portfolio declines around the EA day. A hedge portfolio that buys high-TIR stocks and sells low-TIR stocks 10 days before the EA and holds through the EA earns a 1% return. Most of this return comes from the short side, consistent with investor over-optimism and underreaction to bad news in the Chinese market (Allen *et al.*, 2024), where negative information is more impactful at EAs than positive news.

[19] Additionally, we examine the relationship between our TIR measures and analyst forecast errors (AFE), defined as the difference between realized annual EPS and the consensus forecast made one year earlier, scaled by the year-end stock price (Froot *et al.*, 2017). The results show a positive association, indicating that analysts do not fully incorporate the information contained in TIR.

5.3. The effects of information acquisition

In China, corporate site visits are a common channel for investors—especially financial analysts and institutions—to obtain firm-specific information (Cheng *et al.*, 2016, 2019). These visits allow direct interaction with managers and employees, and firsthand observation of production and operations, potentially exposing information related to TIR and thereby reducing its return predictability.

Empirically, we test whether corporate site visits dampen the EA market reaction to TIR. Firms listed on the SZSE are required to disclose site visit transcripts within two trading days via the EasyIR platform, including the event date, location, and participant details.[20] In contrast, SHSE-listed firms are not subject to the same disclosure requirements, limiting data availability. To supplement this analysis, we use proximity to China's high-speed rail (HSR) network as a proxy for site visit accessibility. Prior research shows that HSR improves site visit frequency and analyst forecast accuracy (Chen *et al.*, 2022). Accordingly, we expect a stronger EA market reaction to TIR for firms located farther from HSR stations.

Using SZSE data, we define a variable $SiteVisit_{i,q}$ that equals 1 if a firm's number of visiting financial institutions in quarter q is in the top decile, and 0 otherwise. For the full sample, we construct a dummy $HSR_{i,q}$ equal to 1 if the average distance between a firm's factories and the nearest HSR station in quarter q is in the top decile, and 0 otherwise. We interact both variables with $DARW_{i,s}$ and include them in the $CAR(-1,1)_{i,q+1}$ regression model. Results are presented in Table OA.7.

Columns (1) and (2) show results using $SiteVisit_{i,q}$. The coefficients on $DARw_{i,q} \times SiteVisit_{i,q}$ are negative, significant at the 5% level. This indicates that the return predictability of TIR is

[20] The disclosures of corporate site visits are available from SZSE's website at http://irm.cninfo.com.cn.

concentrated in firms with low levels of site visit activity. Columns (3) and (4) report the results using $DARw_{i,q} \times HSR_{i,q}$. The coefficients on the interaction terms are significantly positive, indicating that the return predictability of TIR is more pronounced for firms located farther from HSR access points.

Taken together, these results indicate that the return predictability of TIR declines with greater investor information access and increases with higher information acquisition costs. This highlights the particular value of TIR in improving information acquisition for firms located in remote or less accessible regions.

5.4. The effects of corporate transparency

Alternative sources of information become more important when firms' reporting quality is low. Therefore, we anticipate that the return predictability of TIR increases when firms have low reporting transparency. To test this, we measure firms' reporting transparency using the level of earnings management. Previous studies demonstrate that Chinese firms frequently engage in earnings manipulation, which inhibits investors' understanding of firms' fundamentals (Aharony *et al.*, 2000; Chen & Yuan, 2004; Firth *et al.*, 2019).

We follow Kothari *et al.* (2009) and measure earnings management using the absolute value of the residuals obtained from regressing firms' total accruals (i.e., the change in current assets minus the change in cash holding minus the change in current liabilities plus the change in short-term debt plus depreciation, scaled by total assets) on the reciprocal of total assets; the change in sales/total assets; and net property, plant, and equipment/total assets. We create a variable $EM_{i,q}$ that takes a value of 1 if the earnings management of a firm in quarter q is in the top decile, and 0 otherwise. We then estimate the model of $CAR(-1,1)_{i,q+1}$ by adding the interaction between $DARw_{i,q}$ and $EM_{i,q}$. The results are reported in Columns (5) and (6) of Table OA.7. The coefficients on the interaction term are positive and significant at the 5% level. The results indicate that the informational value of TIR increases with the opaqueness of firms' reporting.

6. Conclusion

This paper introduces a novel measure of firm-level operational activities by exploiting TIR emitted by manufacturing firms' factories, leveraging the physical fact that any activities that consume energy emit heat as a fundamental result of the laws of thermodynamics. Utilizing extensive satellite data covering thousands of publicly listed firms' factories in China, we demonstrate that TIR reliably captures real-time operational disruptions, significantly predicts future sales growth, and correlates closely with subsequent capital expenditures, employment, production costs, and profitability.

Crucially, we document that firm-level TIR contains valuable predictive information about future stock returns, especially pronounced for opaque firms and those with limited investor accessibility. Despite its informational value, we find no evidence that sophisticated investors, including institutional investors and short sellers, have integrated this signal into their trading strategies, highlighting TIR as a distinct and underutilized source of market-relevant information.

Overall, this study introduces a direct measure of firms' operating activities in the early stages of the revenue generation process that contains valuable information not yet embedded in stock prices.

References

Aharony, J., Lee, C.-W.J., Wong, T.J., 2000. Financial packaging of IPO firms in China. Journal of Accounting Research 38, 103-126

Allen, F., Qian, J., Shan, C., Zhu, J.L., 2024. Dissecting the long-term performance of the Chinese stock market. The Journal of Finance 79, 993-1054

Axbard, S., 2016. Income opportunities and sea piracy in Indonesia: Evidence from satellite data. American Economic Journal: Applied Economics 8, 154-94

Babenko, B., Hersh, J., Newhouse, D., Ramakrishnan, A., Swartz, T., 2017. Poverty mapping using convolutional neural networks trained on high and medium resolution satellite images, with an application in Mexico. arXiv preprint arXiv:1711.06323

Benou, G., Richie, N., 2003. The reversal of large stock price declines: The case of large firms. Journal of Economics and Finance 27, 19-38

Berg, T., Burg, V., Gombović, A., Puri, M., 2020. On the rise of fintechs: Credit scoring using digital footprints. The Review of Financial Studies 33, 2845-2897

Blankespoor, E., Hendricks, B.E., Piotroski, J., Synn, C., 2022. Real-time revenue and firm disclosure. Review of Accounting Studies 27, 1079-1116

Burchfield, M., Overman, H.G., Puga, D., Turner, M.A., 2006. Causes of sprawl: A portrait from space. The Quarterly Journal of Economics 121, 587-633

Bushee, B.J., Gerakos, J.J., Lee, L.F., 2018. Corporate jets and private meetings with investors. Journal of Accounting and Economics 65, 358-379

Carhart, M.M., 1997. On persistence in mutual fund performance. The Journal of Finance 52, 57-82

Chen, D., Ma, Y., Martin, X., Michaely, R., 2022. On the fast track: Information acquisition costs and information production. Journal of Financial Economics 143, 794-823

Chen, H., De, P., Hu, Y.J., Hwang, B.-H., 2014. Wisdom of crowds: The value of stock opinions transmitted through social media. The Review of Financial Studies 27, 1367-1403

Chen, K.C., Yuan, H., 2004. Earnings management and capital resource allocation: Evidence from China's accounting-based regulation of rights issues. The Accounting Review 79, 645-665

Chen, X., Cheng, Q., Hao, Y., Liu, Q., 2020. GDP growth incentives and earnings management: Evidence from China. Review of Accounting Studies 25, 1-38

Chen, X., Nordhaus, W.D., 2011. Using luminosity data as a proxy for economic statistics. Proceedings of the National Academy of Sciences 108, 8589-8594

Cheng, Q., Du, F., Wang, X., Wang, Y., 2016. Seeing is believing: Analysts' corporate site visits. Review of Accounting Studies 21, 1245-1286

Cheng, Q., Du, F., Wang, X., Wang, Y., 2019. Do corporate site visits impact stock prices? Contemporary Accounting Research 36, 359-388

Clausius, R., 1854. Über eine veränderte Form des zweiten Hauptsatzes der mechanischen Wärmetheorie. Annalen der Physik 169, 481-506

Darrat, A.F., Gilley, O., Wu, Y., Zhong, M., 2010. On the Chinese B-share price discount puzzle: Some new evidence. Journal of Business Research 63, 895-902

Dichev, I.D., Qian, J., 2022. The benefits of transaction-level data: The case of NielsenIQ scanner data. Journal of Accounting and Economics 74, 101495

Engelberg, J.E., Reed, A.V., Ringgenberg, M.C., 2012. How are shorts informed?: Short sellers, news, and information processing. Journal of Financial Economics 105, 260-278

Engstrom, R., Hersh, J., Newhouse, D., 2017. Poverty from space: Using high-resolution satellite imagery for estimating economic well-being. The World Bank

Ermida, S.L., Soares, P., Mantas, V., Göttsche, F.-M., Trigo, I.F., 2020. Google Earth Engine open-source code for land surface temperature estimation from the Landsat series. Remote Sensing 12, 1471

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56

Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1-22

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607-636

Firth, M., Lin, C., Wong, S.M.-l., Zhao, X., 2019. Hello, is anybody there? Corporate accessibility for outside shareholders as a signal of agency problems. Review of Accounting Studies 24, 1317-1358

Froot, K., Kang, N., Ozik, G., Sadka, R., 2017. What do measures of real-time corporate sales say about earnings surprises and post-announcement returns? Journal of Financial Economics 125, 143-162

Geddes, J.A., Martin, R.V., Boys, B.L., van Donkelaar, A., 2016. Long-term trends worldwide in ambient NO2 concentrations inferred from satellite observations. Environmental Health Perspectives 124, 281-289

Georgescu-Roegen, N., 1971. The entropy law and the economic process. Harvard University Press.

Green, T.C., Huang, R., Wen, Q., Zhou, D., 2019. Crowdsourced employer reviews and stock returns. Journal of Financial Economics 134, 236-251

Grieser, W., Hadlock, C.J., Pierce, J.R., 2021. Doing good when doing well: Evidence on real earnings management. Review of Accounting Studies 26, 906-932

Guiteras, R., Jina, A., Mobarak, A.M., 2015. Satellites, self-reports, and submersion: exposure to floods in Bangladesh. American Economic Review 105, 232-36

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S., Goetz, S.J., Loveland, T.R., 2013. High-resolution global maps of 21st-century forest cover change. Science 342, 850-853

Henderson, J.V., Storeygard, A., Weil, D.N., 2012. Measuring economic growth from outer space. American Economic Review 102, 994-1028

Huang, F., Zhang, B., Zhao, X., 2024. The thermodynamics of the economy. Available at SSRN 4393439

Huang, J., 2018. The customer knows best: The investment value of consumer opinions. Journal of Financial Economics 128, 164-182

Huang, K., Li, M., Markov, S., 2020. What do employees know? Evidence from a social media platform. The Accounting Review 95, 199-226

Jean, N., Burke, M., Xie, M., Davis, W.M., Lobell, D.B., Ermon, S., 2016. Combining satellite imagery and machine learning to predict poverty. Science 353, 790-794

Jiang, F., Jiang, Z., Kim, K.A., 2020. Capital markets, financial institutions, and corporate finance in China. Journal of Corporate Finance 63, 101309

Jiang, F., Kim, K.A., 2020. Corporate governance in China: A survey. Review of Finance 24, 733-772

Kang, J.K., Stice-Lawrence, L., Wong, Y.T.F., 2021. The firm next door: Using satellite images

to tease out information acquisition costs. Journal of Accounting Research 59, 713-750
Katona, Z., Painter, M., Patatoukas, P.N., Zeng, J., 2025. On the capital market consequences of alternative data: Evidence from outer space. Journal of Financial and Quantitative Analysis 60, 551 - 579
Kogure, T., Leung, K.-C., 2007. Thermodynamic equilibrium and black-body radiation. Springer.
Kothari, S.P., Shu, S., Wysocki, P.D., 2009. Do managers withhold bad news? Journal of Accounting Research 47, 241-276
Kudamatsu, M., Persson, T., Strömberg, D., 2012. Weather and infant mortality in Africa. Working paper
Lee, J., 2021. Information asymmetry, mispricing and security issuance. Journal of Finance, forthcoming
Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. The Review of Economic Studies 70, 317-341
Li, B., Venkatachalam, M., 2022. Leveraging big data to study information dissemination of material firm events. Journal of Accounting Research 60, 565-606
Lobell, D.B., 2013. The use of satellite data for crop yield gap analysis. Field Crops Research 143, 56-64
Mukherjee, A., Panayotov, G., Shon, J., 2021. Eye in the sky: Private satellites and government macro data. Journal of Financial Economics 141, 234-254
Okorie, O., Subramoniam, R., Charnley, F., Patsavellas, J., Widdifield, D., Salonitis, K., 2020. Manufacturing in the time of COVID-19: An assessment of barriers and enablers. IEEE Engineering Management Review 48, 167-175
Saiz, A., 2010. The geographic determinants of housing supply. The Quarterly Journal of Economics 125, 1253-1296
Solomon, D., Soltes, E., 2015. What are we meeting for? The consequences of private meetings with investors. The Journal of Law and Economics 58, 325-355
Sun, Q., Tong, W.H.S., 2003. China share issue privatization: The extent of its success. Journal of Financial Economics 70, 183-222
Tang, V.W., 2018. Wisdom of crowds: Cross-sectional variation in the informativeness of third-party-generated product information on Twitter. Journal of Accounting Research 56, 989-1034
Thomson, W., 1853. On the dynamical theory of heat, with numerical results deduced from Mr Joule's equivalent of a thermal unit, and M. Regnault's observations on steam. Earth and Environmental Science Transactions of The Royal Society of Edinburgh 20, 261-288
Vanhellemont, Q., 2020a. Automated water surface temperature retrieval from Landsat 8/TIRS. Remote Sensing of Environment 237, 111518
Vanhellemont, Q., 2020b. Combined land surface emissivity and temperature estimation from Landsat 8 OLI and TIRS. ISPRS Journal of Photogrammetry and Remote Sensing 166, 390-402
Yang, J., 2003. Market segmentation and information asymmetry in Chinese stock markets: A VAR analysis. Financial Review 38, 591-609
Zhu, C., 2019. Big data as a governance mechanism. The Review of Financial Studies 32, 2021-2061

Appendix 1. The revenue generation process

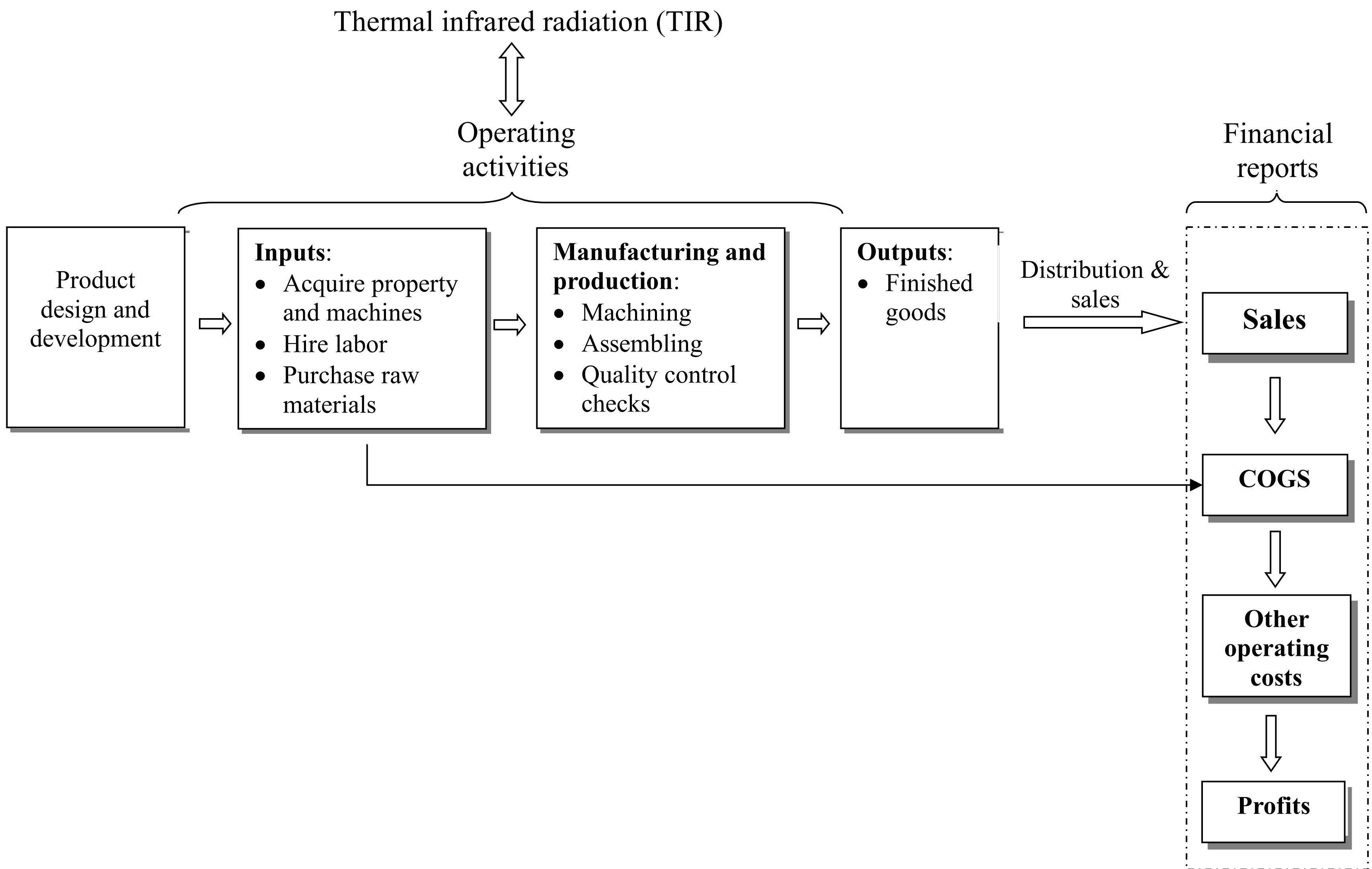
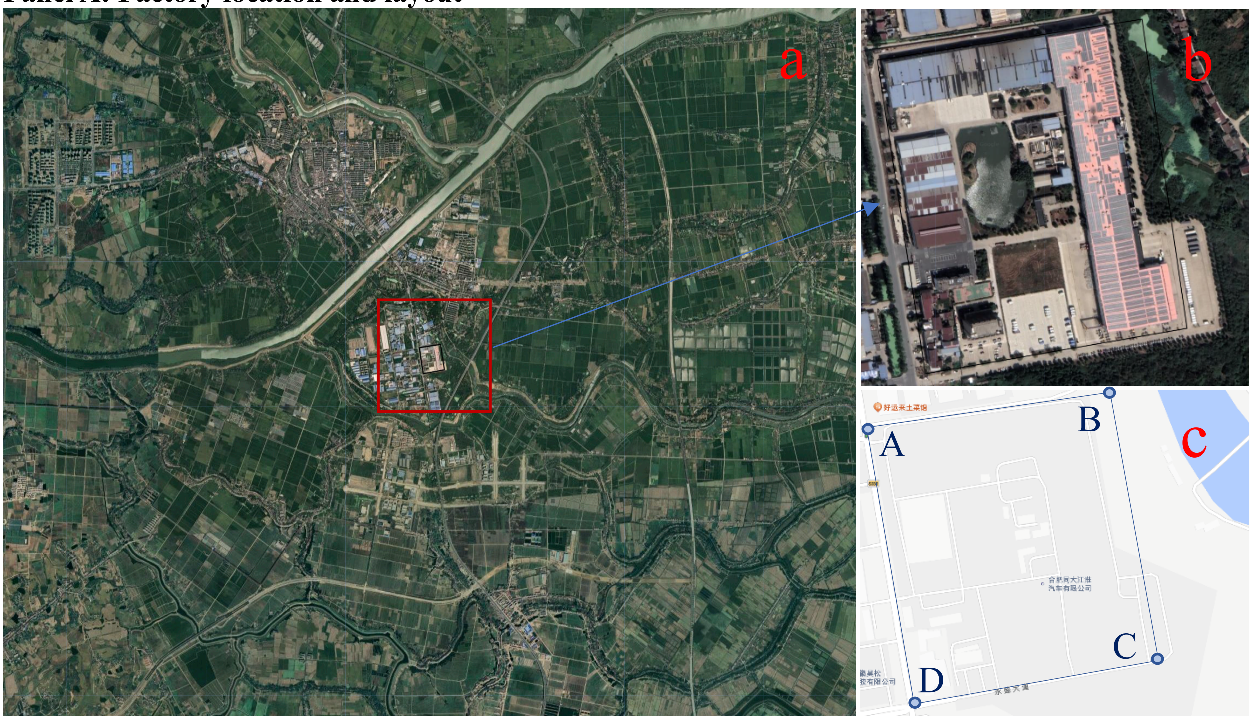


Figure 1. TIR construction illustration

Company: Hefei Tongda Jianghuai Automobile Co., Ltd
Address: Weidang Village, Tongda Town, Lujiang County, Hefei City, Anhui Province
Longitude: 117.2594; Latitude: 31.4908

Panel A: Factory location and layout



Panel B: Thermal infrared radiation (TIR) map

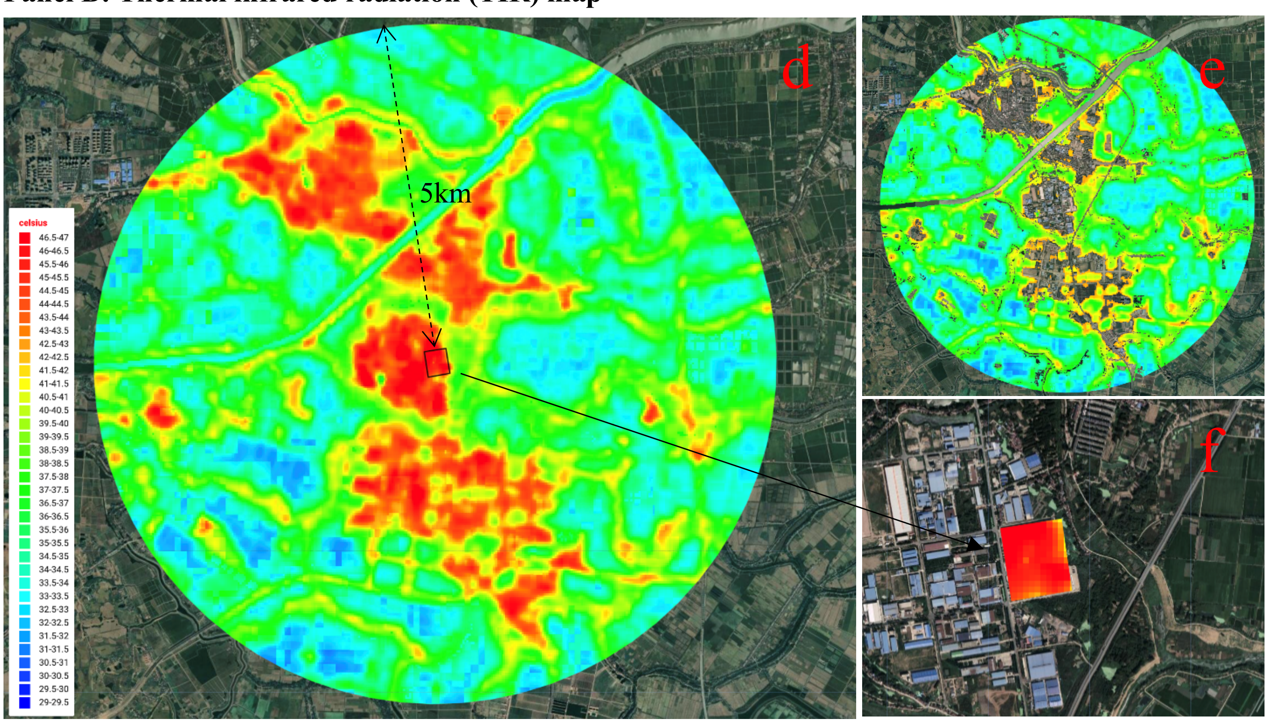
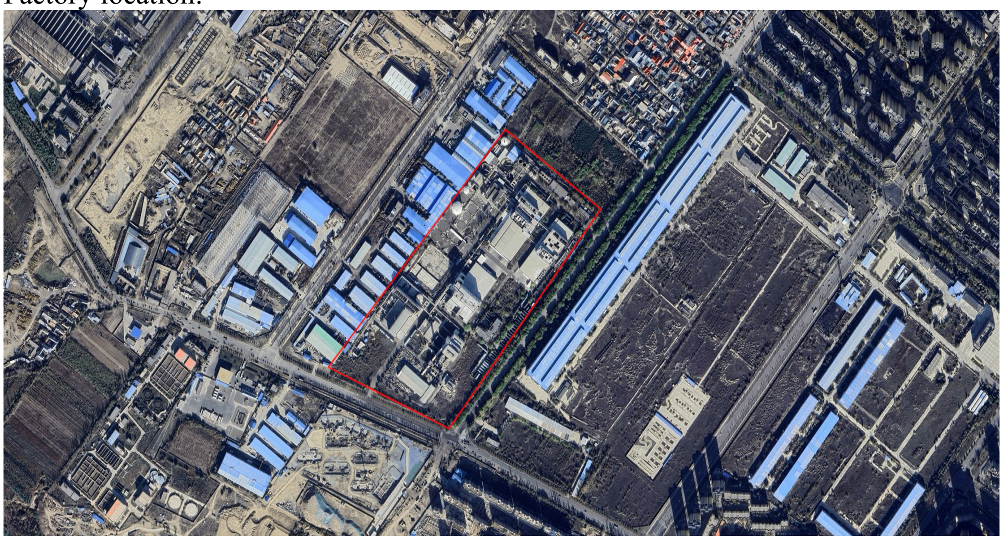


Figure 2. Changes in adjusted TIR during factory shutdowns

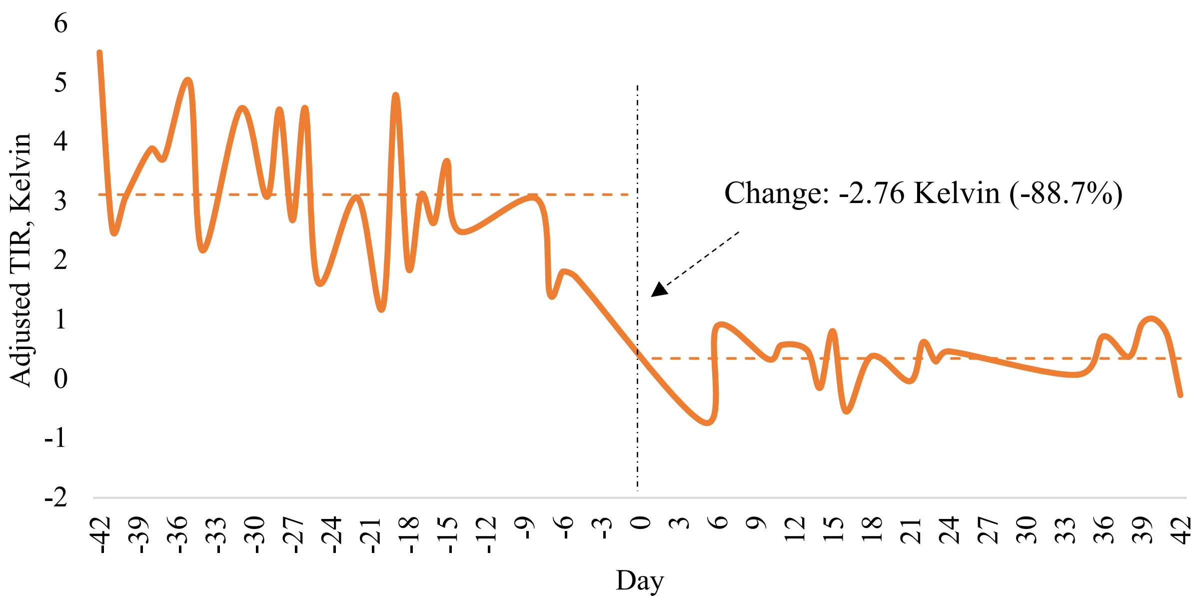
Panel A: Angel Yeast (Ili) Co., LTD factory shutdown

A.1 Factory information and location
Name: Angel Yeast (Ili) Co., LTD
Address: No. 4199, Chongqing Road, Yining City, Yili Kazak Autonomous Prefecture, Xinjiang Uygur Autonomous Region.
Longitude: 81.2340; Latitude: 43.9216
Starting date of shutdown: 10/03/2021
Ending date of shutdown: 11/17/2021

Factory location:



A.2. Daily adjusted TIR around the shutdown



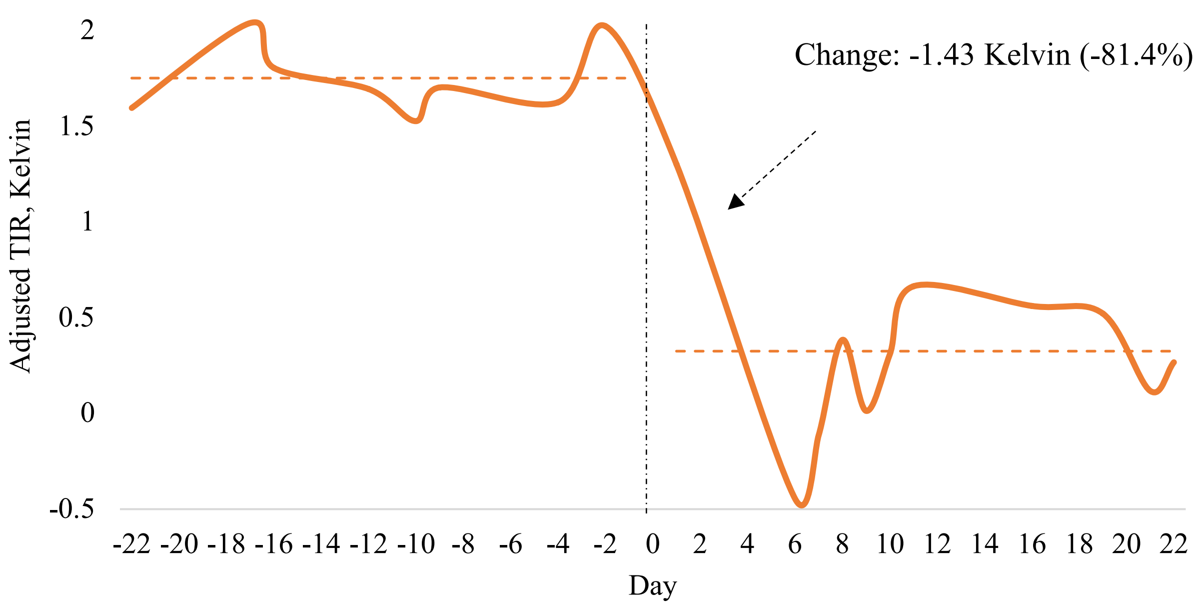
Note: The adjusted TIR is the TIR in the factory area (*FR*) minus TIR of bare lands (*BR*) within a 5 km radius around the factory, excluding the factory area itself (a buffer area). The horizontal lines are the average adjusted TIR before and after the shutdown date. Day 0 indicates the shutdown date.

Panel B: Shijiazhuang Huigu Enterprise Management Co., LTD factory shutdown

B.1 Factory information and location
Name: Shijiazhuang Huigu Enterprise Management Co., LTD
Address: No. 8 Yuanhang Road, Sijiazhuang Village, Sijiazhuang Town, Luquan District, Shijiazhuang City, Hebei Province.
Longitude: 114.4473; Latitude: 37.9470
Starting date of shutdown: 11/02/2021
Ending date of shutdown: 11/15/2021

Factory location:

B.2. Daily adjusted TIR around the shutdown



Note: The adjusted TIR is the TIR in the factory area (*FR*) minus TIR of bare lands (*BR*) within a 5 km radius around the factory, excluding the factory area itself (a buffer area). The horizontal lines are the average adjusted TIR before and after the shutdown date. Day 0 indicates the shutdown date.

Figure 3. Changes in adjusted TIR during Yinan Industrial Park shutdown

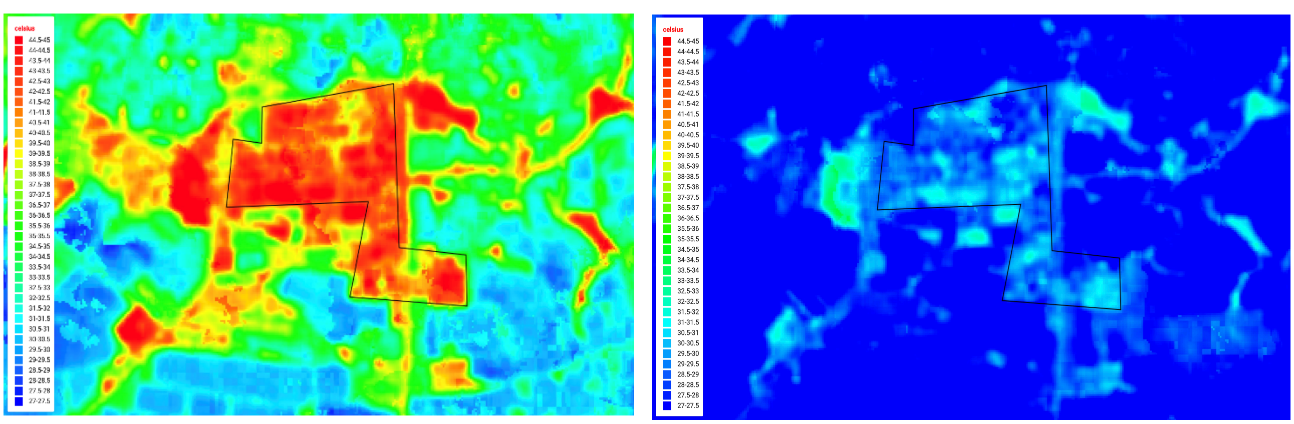
Panel A: Industrial park information and location

Name: Yinan Industrial Park
Address: River Valley Center, Ningshi Development Zone, Yili, Xinjiang
Longitude: 81.1617; Latitude: 43.7760
Starting date of shutdown: 08/03/2022
Ending date of shutdown: 11/16/2022

Park location

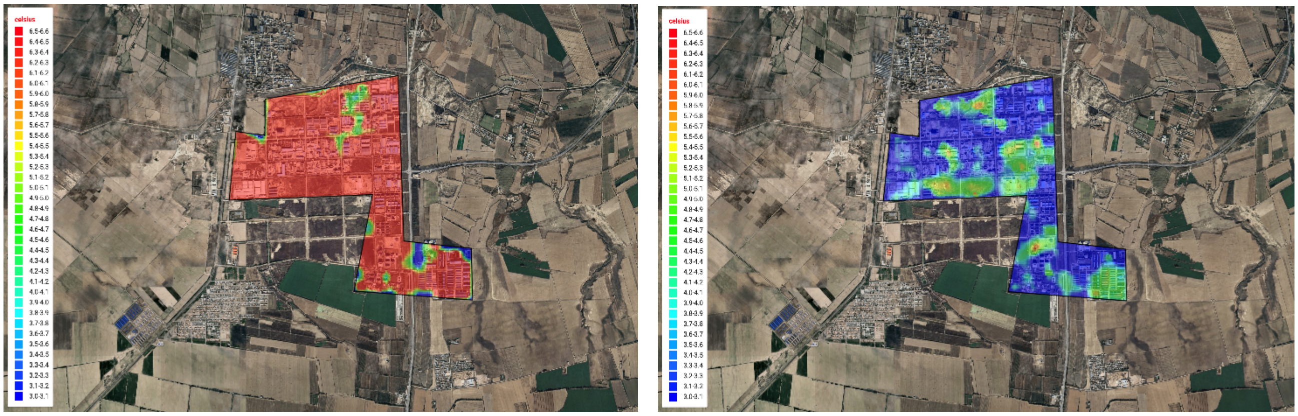
Panel B: TIR before and after the shutdown

Before shutdown | After shutdown



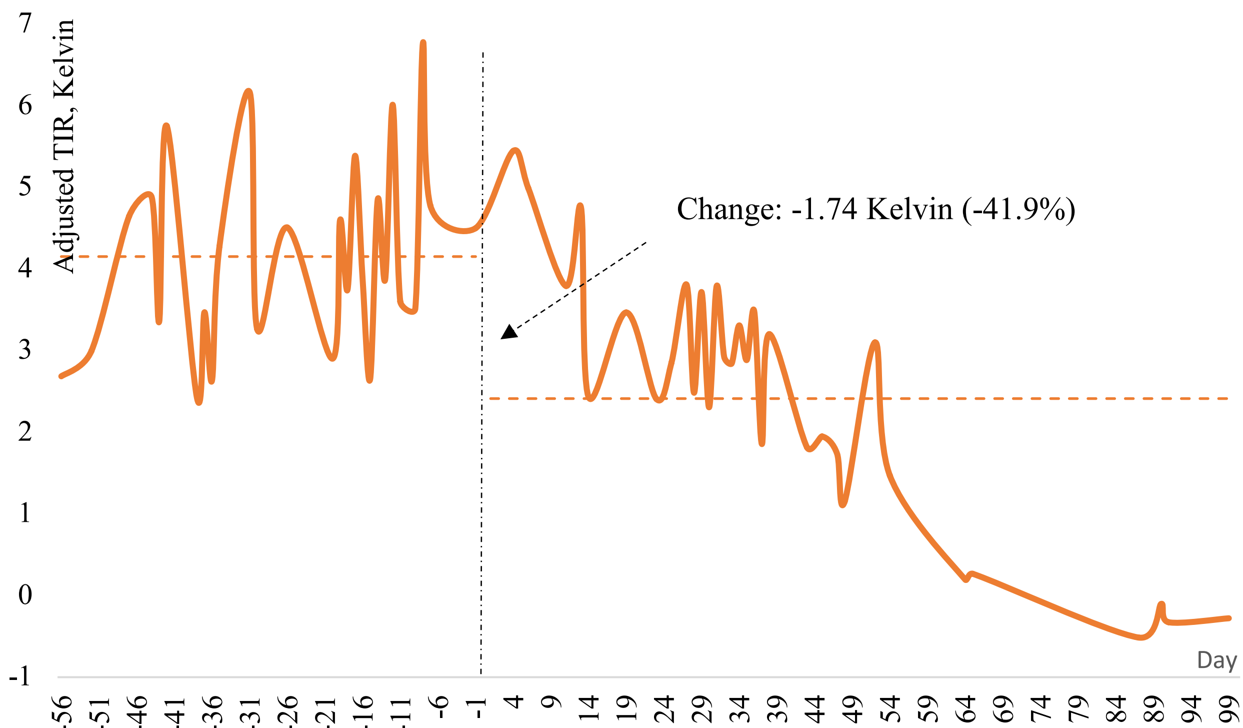
Panel C: Adjusted TIR in the park area before and after the shutdown

Before shutdown　　　　　　　　After shutdown



Animated daily adjusted TIR around the shutdown is available at: https://github.com/edwardzxf/CTIR/blob/main/Yinan%20Park%20shutdown%20in%202022.gif

Panel D: Daily adjusted TIR around the shutdown



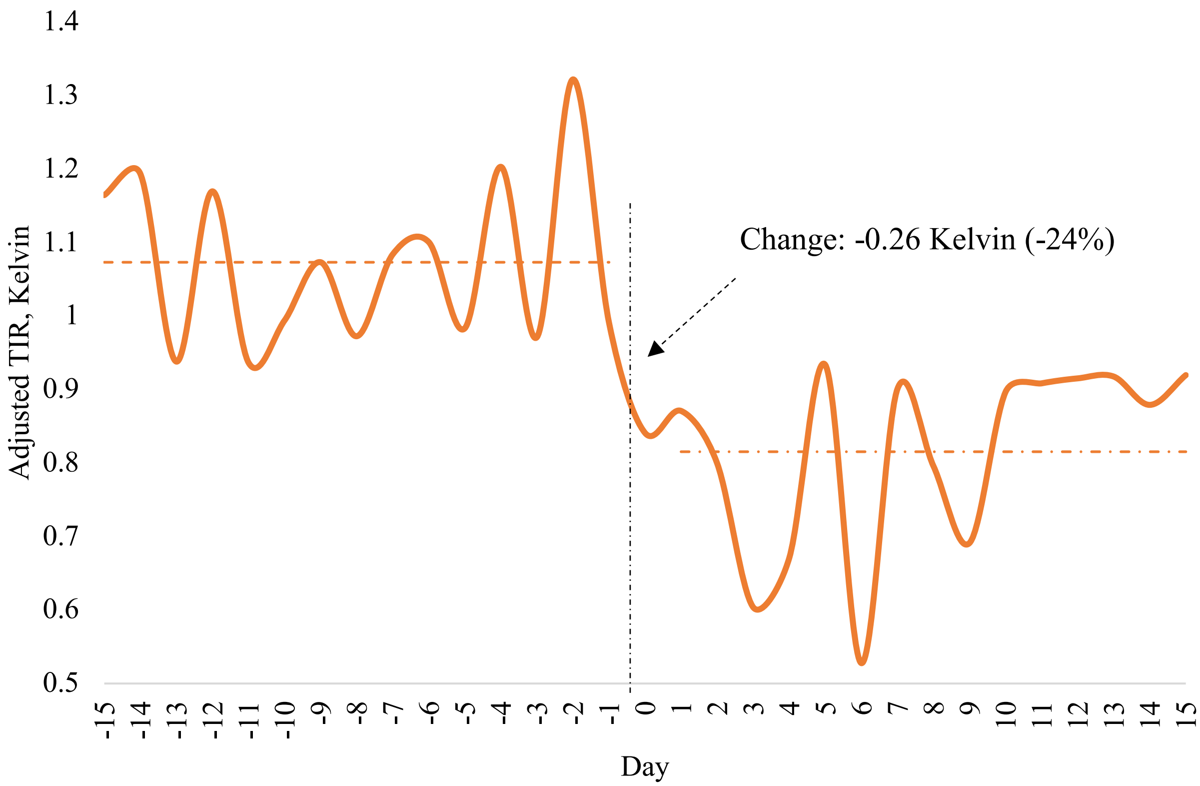
Note: This figure illustrates changes in adjusted TIR for Yinan Industrial Park in Xinjiang around its shutdown period. Panel A shows the park's location overlaid on satellite imagery. Panel B compares unadjusted TIR heatmaps before and after the shutdown, while Panel C displays adjusted TIR maps based on differences from surrounding bare land, which defined as the TIR in the industrial park area ($\boldsymbol{FR}$) minus the TIR of bare lands ($\boldsymbol{BR}$) within a 5 km radius around the park, excluding the park area itself (a buffer area). Panel D charts daily adjusted TIR values. Day 0 is the shutdown date. The horizontal lines are the average adjusted TIR before and after the shutdown date.

Figure 4. Aggregated changes in adjusted TIR during factory shutdowns

Panel A. Incident filtering process

Items	N
Manufacturing listed companies' shutdown incidents during our sample period	**143**
- Exclude incidents without TIR data 15 days before and after shutdown.	-3
- Exclude incidents caused by fires, storms, floods, relocations, and other events that could compromise the accuracy of TIR measurements.	-75
- Exclude incidents with unclear shutdown dates.	-2
- Exclude incidents affecting only partial production lines or products with limited impact on operations.	-7
Final selected shutdown incidents	**56**

Panel B. Daily adjusted TIR around the shutdown of the 56 incidents



Note: This figure presents the selection process and aggregated TIR changes surrounding 56 factory shutdown incidents. Panel A details the screening criteria. Panel B shows the average daily adjusted TIR, measured as the difference between TIR in the factory area and the surrounding bare land within a 5 km radius, from 15 days before to 15 days after each shutdown. Day 0 marks the shutdown date.

Table 1. Variable summary and statistics

Panel A: The factory-level analysis

Variable (1)	Unit (2)	N (3)	Mean (5)	STD (6)	P25 (7)	P50 (8)	P75 (9)
Outcome/TIR variables:							
$AR_{f,q}$	Kelvin	119,904	3.23	3.15	0.90	2.77	5.13
$DAR_{f,q}$	decimal	95,110	0.35	2.42	-0.30	0.01	0.43
Treatment variable:							
$COVID19_{f,q}$	decimal	119,904	1.04	1.88	0.00	0.00	1.39
Control variables:							
$Ret_{f,q}$	%	119,904	7.43	23.22	-8.23	2.31	17.73
$Size_{f,q}$	decimal	119,904	23.06	1.18	22.17	22.85	23.77
$Leverage_{f,q}$	decimal	119,904	0.45	0.17	0.33	0.46	0.58
$Loss_{f,q}$	dummy	119,904	0.14	0.35	0.00	0.00	0.00
$BM_{f,q}$	decimal	119,904	0.72	0.51	0.39	0.61	0.91
$Tangibility_{f,q}$	decimal	119,904	0.23	0.12	0.14	0.22	0.31
$Plants_{f,q}$	integer	119,904	40.38	52.32	12.00	22.00	45.00
$Temperature_{f,q}$	℃	119,904	16.05	8.47	9.44	18.45	22.07
$Humidity_{f,q}$	%	119,904	71.60	11.01	66.06	75.50	78.94
$Precipitation_{f,q}$	mm	119,904	3.21	2.49	1.09	2.64	4.97
$Sunshine_{f,q}$	hours	119,904	5.31	1.78	4.09	5.05	6.51
$GDPGrowth_{f,q}$	%	119,904	6.38	8.03	2.79	5.92	11.44
$GDP/Capita_{f,q}$	ten thousand yuan	119,904	9.91	4.24	6.78	9.35	13.50

Panel B: The firm-level analysis

Variable (1)	Unit (2)	N (3)	Mean (5)	STD (6)	P25 (7)	P50 (8)	P75 (9)
Outcome variables:							
$SG_{i,q+1}$	%	61,346	18.75	53.43	-7.22	9.82	30.98
$COGS_{i,q+1}$	%	61,337	18.21	47.18	-5.73	10.18	30.26
$Employment_{i,y}$	%	17,702	7.38	30.13	-4.56	2.07	12.02
$OperatingMargin_{i,q+1}$	%	61,346	5.51	26.43	1.53	6.99	14.24
$Ret_{i,q+1}$	%	60,639	4.00	24.01	-11.30	-0.33	14.59
$ARet_{i,q+1}$	%	60,639	-3.07	17.42	-13.64	-4.82	5.79
$CAR(-1, 1)_{i,\ q+1}$	%	45,162	-0.24	4.96	-3.13	-0.41	2.38
$DSHO_{i,q}$	decimal	19,822	-0.05	2.46	-0.23	-0.00	0.19
$DIO_{i,q}$	%	61,346	-0.60	6.97	-3.65	-0.55	1.86
TIR variables:							
$DARe_{i,q}$	decimal	61,346	0.32	1.85	-0.21	0.03	0.34
$DARw_{i,q}$	decimal	61,346	0.32	1.87	-0.21	0.03	0.35
$DAReL8_{i,q}$	decimal	61,175	0.31	1.89	-0.22	0.02	0.35
$DARwL8_{i,q}$	decimal	61,175	0.32	1.89	-0.22	0.02	0.35
$DAReT1_{i,q}$	decimal	61,232	0.30	1.76	-0.20	0.03	0.34
$DARwT1_{i,q}$	decimal	61,232	0.31	1.81	-0.20	0.03	0.34
$DAReS_{i,q}$	decimal	56,957	0.35	1.99	-0.21	0.03	0.36
$DARwS_{i,q}$	decimal	56,957	0.36	2.09	-0.21	0.03	0.36
$DAReH_{i,q}$	decimal	55,282	0.35	2.72	-0.31	0.02	0.46
$DAReO_{i,q}$	decimal	51,231	0.37	3.30	-0.34	0.01	0.51
$DARwO_{i,q}$	decimal	51,231	0.37	3.17	-0.34	0.01	0.51
$DAReM_{i,q}$	decimal	61,190	0.13	1.19	-0.17	0.00	0.22

$DARwM_{i,q}$	decimal	61,190	0.13	1.25	-0.17	0.01	0.22
Control variables:							
$Ret_{i,q}$	%	61,346	3.87	24.41	-11.56	-0.67	14.40
$Size_{i,q}$	decimal	61,346	22.67	0.95	21.99	22.51	23.21
$Leverage_{i,q}$	decimal	61,346	0.40	0.19	0.26	0.40	0.54
$Loss_{i,q}$	dummy	61,346	0.17	0.38	0.00	0.00	0.00
$BM_{i,q}$	decimal	61,346	0.58	0.41	0.30	0.49	0.75
$Tangibility_{i,q}$	decimal	61,346	0.22	0.13	0.12	0.20	0.30
$Plants_{i,q}$	integer	61,346	15.17	16.39	5.00	10.00	18.00
$Temperature_{i,q}$	℃	61,346	16.68	8.07	9.90	18.83	23.53
$Humidity_{i,q}$	%	61,346	72.40	8.58	68.51	74.49	78.49
$Precipitation_{i,q}$	mm	61,346	3.40	2.31	1.38	2.92	5.15
$Sunshine_{i,q}$	hours	61,346	5.24	1.37	4.30	5.12	6.13
$GDPGrowth_{i,q}$	%	61,346	7.35	4.68	4.88	7.41	10.25
$GDP/Capita_{i,q}$	ten thousand yuan	61,346	9.52	3.29	7.07	9.17	11.81
Additional variables:							
$Energy_{i,q}$	dummy	61,346	0.10	0.31	0.00	0.00	0.00
$TFP_{i,q}$	dummy	60,220	0.09	0.29	0.00	0.00	0.00
$SOE_{i,q}$	dummy	61,346	0.26	0.44	0.00	0.00	1.00
$SiteVisit_{i,q}$	dummy	39,295	0.10	0.30	0.00	0.00	0.00
$HSR_{i,q}$	dummy	61,346	0.10	0.30	0.00	0.00	0.00
$EM_{i,q}$	dummy	61,321	0.10	0.30	0.00	0.00	0.00

Notes: The table reports the summary statistics of the variables used in this study. Variable definitions and data sources are provided in Table OA.1.

Table 2. TIR and the pandemic outbreak

Dependent variable	$AR_{f,q}$		$DAR_{f,q}$	
	(1)	(2)	(3)	(4)
$COVID19_{f,q}$	**-0.078****	**-0.086*****	**-0.054*****	**-0.057****
	(0.03)	**(0.02)**	**(0.01)**	**(0.02)**
$Ret_{f,q}$		0.001		0.001
		(0.00)		(0.00)
$Size_{f,q}$		-0.023		-0.041
		(0.03)		(0.06)
$Leverage_{f,q}$		-0.087		0.244
		(0.27)		(0.29)
$Loss_{f,q}$		-0.025		-0.098**
		(0.02)		(0.03)
$BM_{f,q}$		-0.007		-0.027
		(0.06)		(0.05)
$Tangibility_{f,q}$		-0.391**		0.803*
		(0.13)		(0.39)
$Plants_{f,q}$		0.001		0.001
		(0.00)		(0.00)
$Temperature_{f,q}$		0.001		0.011
		(0.04)		(0.03)
$Humidity_{f,q}$		0.056***		0.034**
		(0.01)		(0.01)
$Precipitation_{f,q}$		0.074		0.025
		(0.04)		(0.03)
$Sunshine_{f,q}$		0.341***		0.183**
		(0.05)		(0.07)
$GDPGrowth_{f,q}$		-0.000		0.003
		(0.01)		(0.01)
$GDP/Capita_{f,q}$		0.024		0.013
		(0.03)		(0.04)
Factory fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	119,904	119,904	95,110	95,110
R-squared	0.795	0.799	0.148	0.151

Notes: The table reports the estimates of the impact of the pandemic outbreak on corporate TIR. The unit of observation is factory f in a given quarter q. The estimation window is 2019Q1–2021Q2. The dependent variable is the adjusted TIR for factory f, which is the TIR of the factory area minus the TIR of bare lands in the buffer area ($AR_{f,q}$) or the year-over-year change in adjusted TIR for factory f ($DAR_{f,q}$). $COVID19_{f,q}$ is the natural logarithm of 1 plus the number of new COVID-19 infections in factory f's location city in quarter q. We control for the firm characteristics of factory f's listed firm i, which include stock return ($Ret_{i,q}$), firm size ($Size_{i,q}$), financial leverage ($Leverage_{i,q}$), profit status ($Loss_{i,q}$), firm valuation ($BM_{i,q}$), asset tangibility ($Tangibility_{i,q}$), and the number of plants ($Plants_{i,q}$). We also control for the regional characteristics of factory f's location city, which include temperature ($Temperature_{f,q}$), relative humidity ($Humidity_{f,q}$), precipitation ($Precipitation_{f,q}$), sunshine hours ($Sunshine_{f,q}$), GDP growth ($GDPGrowth_{f,q}$), and GDP per capita ($GDP/Capita_{f,q}$). Variable definitions and data sources are provided in Table OA.1. The standard deviations, shown in parentheses, are estimated with clustering at both the city and year-quarter levels. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 3. TIR and sales growth

Dependent variable	$SG_{i,q+1}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DARe_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARw_{i,q}$	
	(1)	(2)	(3)	(4)
$\boldsymbol{DAR_{i,q}}$	**0.292****	**0.314*****	**0.272****	**0.281****
	(0.12)	**(0.11)**	**(0.11)**	**(0.10)**
$Ret_{i,q}$		0.143***		0.143***
		(0.03)		(0.03)
$Size_{i,q}$		11.636***		11.631***
		(1.72)		(1.72)
$Leverage_{i,q}$		32.001***		31.992***
		(5.97)		(5.97)
$Loss_{i,q}$		-11.825***		-11.825***
		(1.09)		(1.09)
$BM_{i,q}$		9.055***		9.041***
		(2.42)		(2.42)
$Tangibility_{i,q}$		-17.362*		-17.353*
		(8.68)		(8.68)
$Plants_{i,q}$		-0.118		-0.118
		(0.08)		(0.08)
$Temperature_{i,q}$		-0.185		-0.185
		(0.13)		(0.13)
$Humidity_{i,q}$		-0.160*		-0.158*
		(0.08)		(0.08)
$Precipitation_{i,q}$		0.399*		0.399*
		(0.21)		(0.21)
$Sunshine_{i,q}$		0.017		0.022
		(0.48)		(0.48)
$GDPGrowth_{i,q}$		0.040		0.041
		(0.09)		(0.09)
$GDP/Capita_{i,q}$		-0.331		-0.331
		(0.27)		(0.27)
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	61,346	61,346	61,346	61,346
R-squared	0.185	0.202	0.185	0.202

Notes: The table reports the estimates for the relationship between corporate TIR and sales growth. The unit of observation is firm *i* in a given year-quarter *q*. The estimation window is 2014Q2–2022Q4. The dependent variable is a firm's sales growth in quarter $q+1$ ($SG_{i,q+1}$). The TIR measures are the year-over-year change in the equally weighted average of adjusted TIR across all factories of a firm in quarter *q* ($DARe_{i,q}$) and the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter *q* ($DARw_{i,q}$). The control variables are the stock return ($Ret_{i,q}$), firm size ($Size_{i,q}$), financial leverage ($Leverage_{i,q}$), profit status ($Loss_{i,q}$), firm valuation ($BM_{i,q}$), asset tangibility ($Tangibility_{i,q}$), number of plants ($Plants_{i,q}$), temperature ($Temperature_{i,q}$), relative humidity ($Humidity_{i,q}$), precipitation ($Precipitation_{i,q}$), sunshine hours ($Sunshine_{i,q}$), GDP growth ($GDPGrowth_{i,q}$), and GDP per capita ($GDP/Capita_{i,q}$). Variable definitions and data sources are provided in Table OA.1. The standard deviations, shown in parentheses, are estimated with clustering at both the firm and year-quarter levels. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 4. The dynamic relationship between TIR and sales growth

Panel A. Equally weighted TIR

Dependent variable	$SG_{i,q-1}$	$SG_{i,q}$	$SG_{i,q+1}$	$SG_{i,q+2}$	$SG_{i,q+3}$	$SG_{i,q+4}$	$SG_{i,q+5}$	$SG_{i,q+6}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$DARe_{i,q}$	-0.035	0.042	**0.314*** **	**0.289** **	**0.310** **	0.206	0.003	-0.004
	(0.14)	(0.09)	**(0.11)**	**(0.14)**	**(0.14)**	(0.16)	(0.11)	(0.14)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,252	61,239	61,346	60,908	58,257	55,734	53,399	50,995
R-squared	0.220	0.234	0.202	0.198	0.207	0.238	0.245	0.251

Panel B. Investment-weighted TIR

Dependent variable	$SG_{i,q-1}$	$SG_{i,q}$	$SG_{i,q+1}$	$SG_{i,q+2}$	$SG_{i,q+3}$	$SG_{i,q+4}$	$SG_{i,q+5}$	$SG_{i,q+6}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$DARw_{i,q}$	-0.055	0.138	**0.281** **	**0.310***	**0.278***	0.136	-0.018	-0.025
	(0.13)	(0.11)	**(0.10)**	**(0.16)**	**(0.14)**	(0.16)	(0.09)	(0.13)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,252	61,239	61,346	60,908	58,257	55,734	53,399	50,995
R-squared	0.220	0.234	0.202	0.198	0.207	0.238	0.245	0.251

Notes: The table reports the estimates for the dynamic relationship between corporate TIR and sales growth. The unit of observation is firm *i* in a given year-quarter *q*. The estimation window is 2014Q2–2022Q4. The dependent variable is a firm's sales growth in quarter $q+n$ ($SG_{i,q+n}$, n = –1, 0, 1, 2, 3, 4, 5, and 6). The TIR measures are the year-over-year change in the equally weighted average of adjusted TIR across all factories of a firm in quarter q ($DARe_{i,q}$) (Panel A) and the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter q ($DARw_{i,q}$) (Panel B). The control variables are the stock return ($Ret_{i,q}$), firm size ($Size_{i,q}$), financial leverage ($Leverage_{i,q}$), profit status ($Loss_{i,q}$), firm valuation ($BM_{i,q}$), asset tangibility ($Tangibility_{i,q}$), number of plants ($Plants_{i,q}$), temperature ($Temperature_{i,q}$), relative humidity ($Humidity_{i,q}$), precipitation ($Precipitation_{i,q}$), sunshine hours ($Sunshine_{i,q}$), GDP growth ($GDPGrowth_{i,q}$), and GDP per capita ($GDP/Capita_{i,q}$). Variable definitions and data sources are provided in Table OA.1. The standard deviations, shown in parentheses, are estimated with clustering at both the firm and year-quarter levels. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 5. TIR and other firm operating activities

Panel A. Costs of goods sold

Dependent variable	$COGS_{i,q+1}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DARe_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARw_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**0.200***	**0.218****	**0.209****	**0.213****
	(0.10)	**(0.09)**	**(0.10)**	**(0.09)**
Control	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	61,337	61,337	61,337	61,337
R-squared	0.190	0.207	0.190	0.207

Panel B. Capital expenditures

Dependent variable	$Capx_{i,q+1}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DARe_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARw_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**0.005****	**0.005****	**0.005****	**0.005***
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**
Control	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	59,666	59,666	59,666	59,666
R-squared	0.433	0.457	0.433	0.457

Panel C. Employment

Dependent variable	$Employment_{i,y}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DARe_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARw_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**1.292****	**1.222****	**1.095****	**1.037****
	(0.50)	**(0.45)**	**(0.47)**	**(0.43)**
Control	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	17,702	17,702	17,702	17,702
R-squared	0.215	0.253	0.214	0.253

Panel D. Operating margin

Dependent variable	$OperatingMargin_{i,q+1}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DARe_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARw_{i,q}$	

	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**0.053**	**0.053***	**0.063***	**0.061****
	(0.03)	**(0.03)**	**(0.03)**	**(0.03)**
Control	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	61,346	61,346	61,346	61,346
R-squared	0.283	0.312	0.283	0.312

Notes: The table reports the estimates for the relationship between TIR and alternative measures of firm operating activities. In Panels A, B, and D, the unit of observation is firm *i* in a given year-quarter *q*. The estimation window is 2014Q2–2022Q4. The alternative measures of operating activities include a firm's growth of costs of goods sold $COGS_{i,q+1}$ (Panel A), capital expenditures $Capx_{i,q+1}$ (Panel B), and operating margin $OperatingMargin_{i,q+1}$ (Panel D). The TIR measures are the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter *q* ($DARe_{i,q}$) and the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter *q* ($DARw_{i,q}$). The control variables are the stock return ($Ret_{i,q}$), firm size ($Size_{i,q}$), financial leverage ($Leverage_{i,q}$), profit status ($Loss_{i,q}$), firm valuation ($BM_{i,q}$), asset tangibility ($Tangibility_{i,q}$), number of plants ($Plants_{i,q}$), temperature ($Temperature_{i,q}$), relative humidity ($Humidity_{i,q}$), precipitation ($Precipitation_{i,q}$), sunshine hours ($Sunshine_{i,q}$), GDP growth ($GDPGrowth_{i,q}$), and GDP per capita ($GDP/Capita_{i,q}$). Variable definitions and data sources are provided in Table OA.1. The standard deviations, shown in parentheses, are estimated with clustering at both the firm and year-quarter levels.

In Panel C, the unit of observation is firm *i* in a given year *y* (data on employment is available solely at the annual level). The estimation window is 2014–2022. The alternative measure of operating activities is firms' employment growth $Employment_{i,y}$ in year *y*. The TIR measures are the year-over-year change in the equally weighted average of adjusted TIR across all factories of a firm in year *y* ($DARe_{i,y}$) and the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in year *y* ($DARw_{i,y}$). The control variables are measured in year *y*. The standard deviations, shown in parentheses, are estimated with clustering at both the firm and year levels. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 6. Fama–MacBeth regression

Panel A. Raw returns

Dependent variable	$Ret_{i,q+1}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DARe_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARw_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**0.131****	**0.111****	**0.128****	**0.101****
	(0.05)	**(0.04)**	**(0.05)**	**(0.04)**
$Ret_{i,q}$		-0.049***		-0.049***
		(0.02)		(0.02)
$Size_{i,q}$		-1.420		-1.421
		(1.16)		(1.16)
$Leverage_{i,q}$		2.392*		2.391*
		(1.19)		(1.19)
$Loss_{i,q}$		-3.843***		-3.840***
		(0.52)		(0.52)
$BM_{i,q}$		1.374**		1.377**
		(0.53)		(0.53)
$Tangibility_{i,q}$		1.035		1.014
		(2.25)		(2.26)
$Plants_{i,q}$		0.008		0.008
		(0.01)		(0.01)
$Temperature_{i,q}$		-0.009		-0.010
		(0.05)		(0.05)
$Humidity_{i,q}$		0.034*		0.036*
		(0.02)		(0.02)
$Precipitation_{i,q}$		-0.254*		-0.253*
		(0.13)		(0.13)
$Sunshine_{i,q}$		-0.036		-0.033
		(0.17)		(0.17)
$GDPGrowth_{i,q}$		0.028		0.029
		(0.03)		(0.03)
$GDP/Capita_{i,q}$		0.018		0.016
		(0.04)		(0.04)
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	60,639	60,639	60,639	60,639
R-squared	0.076	0.151	0.076	0.151

Panel B. Abnormal returns

Dependent variable	$ARet_{i,q+1}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DARe_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARw_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**0.098****	**0.111*****	**0.101****	**0.110*****
	(0.05)	**(0.04)**	**(0.04)**	**(0.03)**
$Ret_{i,q}$		-0.057***		-0.057***
		(0.01)		(0.01)
$Size_{i,q}$		0.075		0.074

		(0.29)		(0.29)
Leverage$_{i,q}$		2.780***		2.778***
		(0.85)		(0.85)
Loss$_{i,q}$		-3.989***		-3.986***
		(0.54)		(0.54)
BM$_{i,q}$		-0.740		-0.739
		(1.62)		(1.62)
Tangibility$_{i,q}$		1.906		1.885
		(1.84)		(1.84)
Plants$_{i,q}$		0.019*		0.019*
		(0.01)		(0.01)
Temperature$_{i,q}$		-0.002		-0.002
		(0.05)		(0.05)
Humidity$_{i,q}$		0.027		0.029
		(0.02)		(0.02)
Precipitation$_{i,q}$		-0.184		-0.184
		(0.13)		(0.13)
Sunshine$_{i,q}$		0.000		0.004
		(0.16)		(0.16)
GDPGrowth$_{i,q}$		0.020		0.021
		(0.03)		(0.03)
GDP/Capita$_{i,q}$		0.030		0.029
		(0.04)		(0.04)
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	60,639	60,639	60,639	60,639
R-squared	0.069	0.108	0.069	0.108

Notes: The table reports the estimates of the Fama–MacBeth regressions. The unit of observation is firm *i* in a given year-quarter *q*. The estimation window is 2014Q2–2022Q4. The dependent variable is a firm's raw stock return in quarter *q+1* ($Ret_{i,q+1}$) (Panel A), or the firm's raw returns minus the returns of the corresponding 5 × 5 market value and book-to-market (Size/BM) matched portfolio in quarter *q+1* ($ARet_{i,q+1}$) (Panel B). The TIR measures are the year-over-year change in the equally weighted average of adjusted TIR across all factories of a firm in quarter *q* ($DARe_{i,q}$) and the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter *q* ($DARw_{i,q}$). The control variables are the stock return ($Ret_{i,q}$), firm size ($Size_{i,q}$), financial leverage ($Leverage_{i,q}$), profit status ($Loss_{i,q}$), firm valuation ($BM_{i,q}$), asset tangibility ($Tangibility_{i,q}$), number of plants ($Plants_{i,q}$), temperature ($Temperature_{i,q}$), relative humidity ($Humidity_{i,q}$), precipitation ($Precipitation_{i,q}$), sunshine hours ($Sunshine_{i,q}$), GDP growth ($GDPGrowth_{i,q}$), and GDP per capita ($GDP/Capita_{i,q}$). Variable definitions and data sources are provided in Table OA.1. We run a cross-sectional regression in each quarter and report the time-series averages of the cross-sectional regression coefficients. The Newey–West standard errors are reported in parentheses. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 7. Portfolio analysis

Panel A. Equally weighted TIR

	Excess	FF3	Carhart4	FF5
Portfolio	(1)	(2)	(3)	(4)
Low *DAR*	1.963	1.082	1.014	1.093
2	2.028	1.206	1.150	1.193
3	2.170	1.369	1.266	1.325
4	2.272	1.446	1.368	1.406
High *DAR*	2.366	1.476	1.383	1.548
High – Low	**0.403****	**0.394****	**0.369***	**0.455****
	(0.19)	**(0.19)**	**(0.19)**	**(0.19)**

Panel B. Investment-weighted TIR

	Excess	FF3	Carhart4	FF5
Portfolio	(1)	(2)	(3)	(4)
Low *DAR*	1.928	1.067	0.999	1.075
2	1.995	1.184	1.138	1.148
3	2.250	1.440	1.353	1.425
4	2.295	1.455	1.359	1.426
High *DAR*	2.356	1.462	1.371	1.522
High – Low	**0.427****	**0.395****	**0.372***	**0.447****
	(0.20)	**(0.20)**	**(0.20)**	**(0.20)**

Notes: This table reports the abnormal returns (i.e., alphas) of portfolios sorted by corporate TIR. For each month m from 2014Q2 to 2022Q4, we sort our sample stocks into quintile portfolios based on $DAR_{i,m}$, which is the year-over-year change in adjusted TIR across all factories of a firm, constructed over the past three months or quarter. We create a zero-cost hedge portfolio that buys stocks in the top quintile (P5) of $DAR_{i,m}$ and sells stocks in the bottom quintile (P1). The performance of the portfolios is tracked over the following month ($m+1$). Value-weighted monthly returns (%) are computed for each portfolio. The excess return of a portfolio is the constant obtained from the model that regresses the portfolio's returns on the risk-free rate (Column (1)). The alpha of a portfolio is the constant obtained from the model that regresses the hedge portfolio's returns or the excess return (raw return minus the risk-free rate) of P1-P5 on the Fama–French three factors (FF3) (Column (2)), the Fama–French–Carhart four factors (Carhart4) (Column (3)), and the Fama–French five factors (FF5) (Column (5)). In Panel A, $DAR_{i,m}$ is the year-over-year change in the equally weighted average of adjusted TIR across all factories of a firm, averaged over the past three months ($DARe_{i,m}$). In Panel B, $DAR_{i,m}$ is the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm, averaged over the past three months ($DARw_{i,m}$). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8. TIR and sophisticated investors

Panel A. Short-selling activities				
Dependent variable	$DSHO_{i,q}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DARe_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARw_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**-0.006**	**-0.007**	**-0.012**	**-0.013**
	(0.01)	**(0.01)**	**(0.01)**	**(0.01)**
$Ret_{i,q}$		0.004**		0.004**
		(0.00)		(0.00)
$Size_{i,q}$		-0.043		-0.043
		(0.09)		(0.09)
$Leverage_{i,q}$		-0.100		-0.097
		(0.26)		(0.26)
$Loss_{i,q}$		0.030		0.029
		(0.06)		(0.06)
$BM_{i,q}$		-0.078		-0.078
		(0.08)		(0.08)
$Tangibility_{i,q}$		0.250		0.249
		(0.58)		(0.58)
$Plants_{i,q}$		-0.004***		-0.004***
		(0.00)		(0.00)
$Temperature_{i,q}$		0.002		0.002
		(0.01)		(0.01)
$Humidity_{i,q}$		0.010		0.010
		(0.01)		(0.01)
$Precipitation_{i,q}$		-0.012		-0.012
		(0.02)		(0.02)
$Sunshine_{i,q}$		0.071		0.071
		(0.08)		(0.08)
$GDPGrowth_{i,q}$		-0.004		-0.004
		(0.00)		(0.00)
$GDP/Capita_{i,q}$		0.011		0.011
		(0.01)		(0.01)
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	19,822	19,822	19,822	19,822
R-squared	0.142	0.143	0.142	0.143

Panel B. Institutional ownership				
Dependent variable	$DIO_{i,q}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DARe_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARw_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**0.028**	**0.032***	**0.027**	**0.029**
	(0.02)	**(0.02)**	**(0.02)**	**(0.02)**
$Ret_{i,q}$		0.039***		0.039***
		(0.00)		(0.00)

$Size_{i,q}$		2.089***		2.089***
		(0.21)		(0.21)
$Leverage_{i,q}$		0.437		0.436
		(0.69)		(0.69)
$Loss_{i,q}$		-0.387***		-0.387***
		(0.10)		(0.10)
$BM_{i,q}$		1.757***		1.756***
		(0.33)		(0.33)
$Tangibility_{i,q}$		0.794		0.795
		(1.09)		(1.09)
$Plants_{i,q}$		-0.009		-0.009
		(0.01)		(0.01)
$Temperature_{i,q}$		0.001		0.001
		(0.01)		(0.01)
$Humidity_{i,q}$		-0.013		-0.012
		(0.01)		(0.01)
$Precipitation_{i,q}$		-0.044		-0.044
		(0.04)		(0.04)
$Sunshine_{i,q}$		-0.103		-0.102
		(0.07)		(0.07)
$GDPGrowth_{i,q}$		-0.027**		-0.027**
		(0.01)		(0.01)
$GDP/Capita_{i,q}$		0.030		0.030
		(0.04)		(0.04)
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	61,346	61,346	61,346	61,346
R-squared	0.122	0.148	0.122	0.148

Notes: The table reports the estimates for the relationship between TIR and the trading activities of sophisticated inventors. The unit of observation is firm *i* in a given year-quarter *q*. The estimation window is 2014Q2–2022Q4. In Panel A, the dependent variable is a firm's net short position change in quarter *q* ($DSHO_{i,q}$), which is the average daily net short position ((short interest opened – short interest closed)/total trading volume) of firm *i* in quarter *q* minus average daily net short position of in quarter *q–4*, multiplied by 1,000. In Panel B, the dependent variable is a firm's intuitional ownership change in quarter *q* ($DIO_{i,q}$), which is the percentage of shares held by institutional ownership of firm *i* in quarter *q* minus the percentage of shares held by institutional ownership of in quarter *q–4*. The TIR measures are the year-over-year change in the equally weighted average of adjusted TIR across all factories of a firm in quarter *q* ($DARe_{i,q}$) and the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter *q* ($DARw_{i,q}$). The control variables are the stock return ($Ret_{i,q}$), firm size ($Size_{i,q}$), financial leverage ($Leverage_{i,q}$), profit status ($Loss_{i,q}$), firm valuation ($BM_{i,q}$), asset tangibility ($Tangibility_{i,q}$), number of plants ($Plants_{i,q}$), temperature ($Temperature_{i,q}$), relative humidity ($Humidity_{i,q}$), precipitation ($Precipitation_{i,q}$), sunshine hours ($Sunshine_{i,q}$), GDP growth ($GDPGrowth_{i,q}$), and GDP per capita ($GDP/Capita_{i,q}$). Variable definitions and data sources are provided in Table OA.1. The standard deviations, shown in parentheses, are estimated with clustering at both the firm and year-quarter levels. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 9. The heterogeneity of the relationship between TIR and sales growth

Dependent variable	$SG_{i,q+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{DARw_{i,q} \times Energy_{i,q}}$	**1.104***	**1.035***				
	(0.60)	**(0.59)**				
$Energy_{i,q}$	1.541	1.126				
	(2.41)	(2.41)				
$\boldsymbol{DARw_{i,q} \times TFP_{i,q}}$			**1.120****	**0.975***		
			(0.52)	**(0.49)**		
$TFP_{i,q}$			10.278***	9.022***		
			(1.39)	(1.37)		
$\boldsymbol{DARw_{i,q} \times SOE_{i,q}}$					**-0.479***	**-0.497***
					(0.26)	**(0.26)**
$SOE_{i,q}$					-10.938***	-8.202***
					(2.66)	(2.81)
$DARw_{i,q}$	0.157	0.173	0.179	0.202*	0.410***	0.424***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.14)	(0.14)
Control	No	Yes	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,346	61,346	60,220	60,220	61,346	61,346
R-squared	0.185	0.202	0.189	0.206	0.185	0.203

Notes: The table reports the estimates for the heterogeneity of the relationship between TIR and corporate sales growth. The unit of observation is firm *i* in a given year-quarter *q*. The estimation window is 2014Q2–2022Q4. The dependent variable is a firm's sales growth in quarter $q+1$ ($SG_{i,q+1}$). The TIR measure is the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter *q* ($DARw_{i,q}$). $Energy_{i,q}$ takes a value of 1 if the energy efficiency for the industry of firm *i* in quarter *q* is in the top decile and 0 otherwise. Energy efficiency is defined as the total sales of the industry to which firm *i* belongs scaled by the total energy consumption of the industry. $TFP_{i,q}$ takes a value of 1 if firm *i*'s TFP calculated based on the Levinsohn and Petrin (2003) (LP) method in quarter *q* is in the top decile, and 0 otherwise. $SOE_{i,q}$ takes a value of 1 if firm *i* is ultimately owned by the state government in quarter *q*, and 0 otherwise. The control variables are the stock return ($Ret_{i,q}$), firm size ($Size_{i,q}$), financial leverage ($Leverage_{i,q}$), profit status ($Loss_{i,q}$), firm valuation ($BM_{i,q}$), asset tangibility ($Tangibility_{i,q}$), number of plants ($Plants_{i,q}$), temperature ($Temperature_{i,q}$), relative humidity ($Humidity_{i,q}$), precipitation ($Precipitation_{i,q}$), sunshine hours ($Sunshine_{i,q}$), GDP growth ($GDPGrowth_{i,q}$), and GDP per capita ($GDP/Capita_{i,q}$). Variable definitions and data sources are provided in Table OA.1. The standard deviations, shown in parentheses, are estimated with clustering at both the firm and year-quarter levels. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Online Appendix

Nowcasting Firms' Operating Activities from Satellite Data on Thermal Infrared Radiation

Figure OA.1. Procedure for computing corporate TIR

Step 1: Calculate the adjusted TIR at the factory level.
The adjusted TIR ($AR_{f,t}$) for factory *f* at time *t* is defined as the difference between the factory's TIR ($FR_{f,t}$) and the TIR of the surrounding buffer area ($BR_{f,t}$):

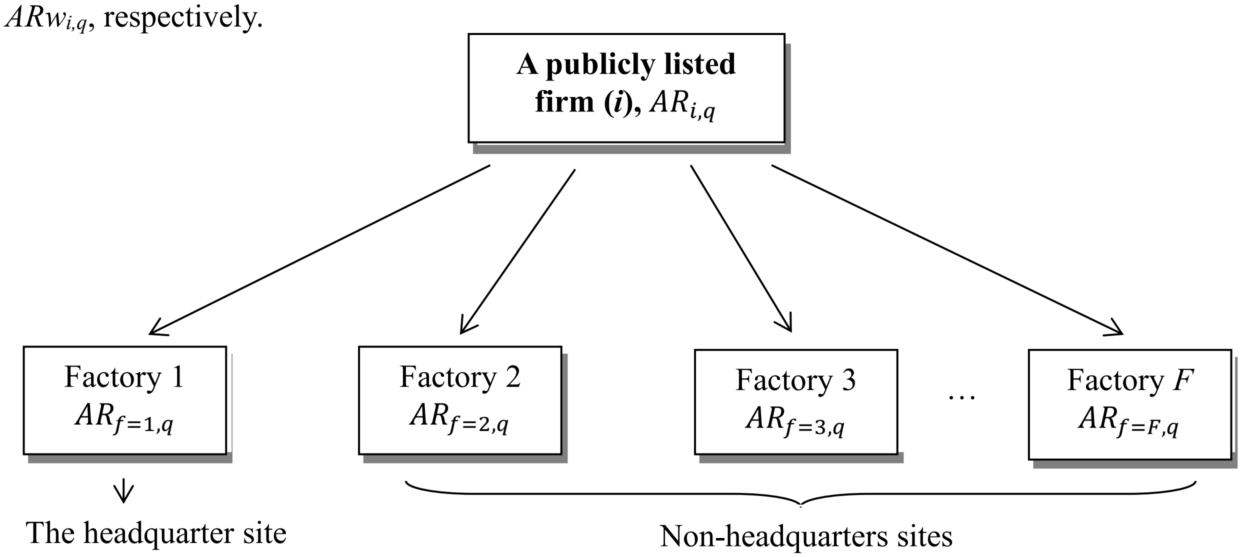
$$AR_{f,t} = FR_{f,t} - BR_{f,t} \qquad (1)$$

Step 2: Compute the quarterly adjusted TIR for each factory.
The quarterly adjusted TIR ($AR_{f,q}$) for factory *f* is obtained by averaging the daily $AR_{f,t}$ values within quarter q.

Step 3: Compute the corporate-level adjusted TIR.
The adjusted TIR for firm i ($AR_{i,q}$) is calculated as either an equally weighted or investment-weighted average of the quarterly factory-level TIRs ($AR_{i,f}$) across all factories (*F*) owned by the firm in a given quarter *q*:

$$AR_{i,q} = \sum_{f=1}^{F} W_f \cdot AR_{f,q} \qquad (2)$$

Here, W_f represents factory *f*'s initial investment as a proportion of the firm's total investment across all factories (investment-weighted) or is equal to 1/*F* (equally weighted). The equally weighted and investment-weighted versions of the firm's adjusted TIR are denoted as $ARe_{i,q}$ and $ARw_{i,q}$, respectively.

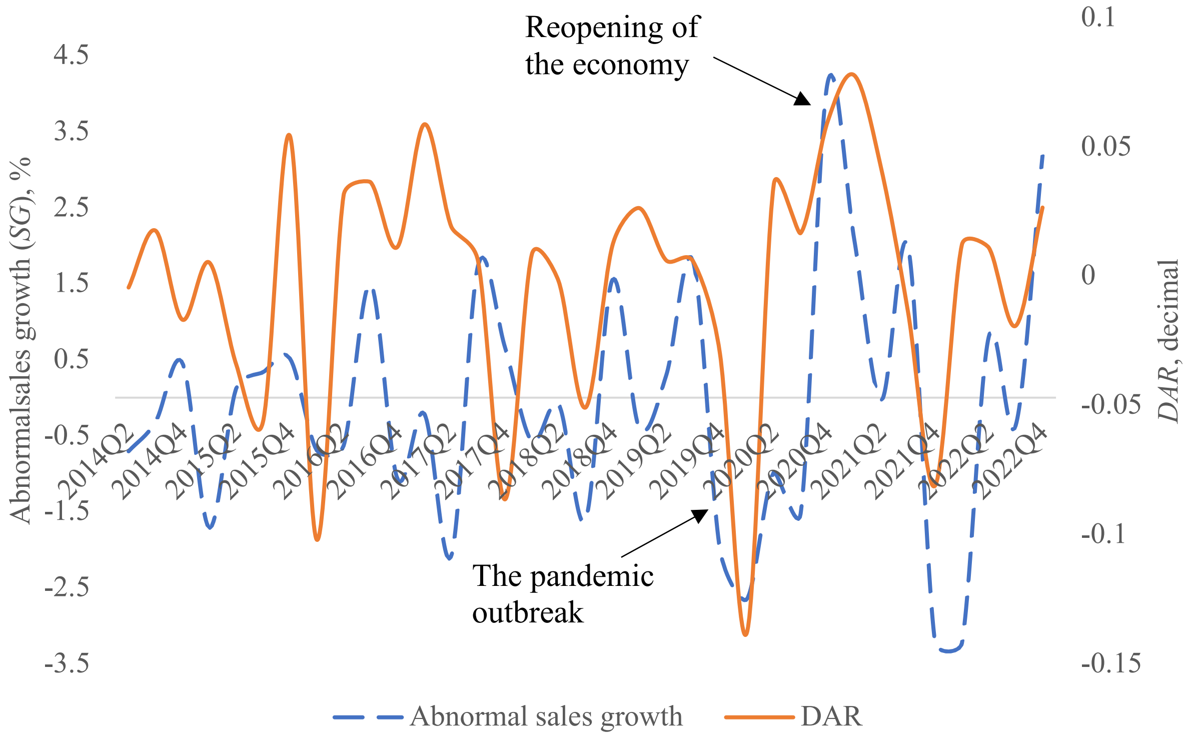


Step 4: Calculate the year-over-year change in adjusted TIR ($DAR_{i,q}$).
The firm-level year-over-year change ($DAR_{i,q}$) is defined as the difference between the firm's adjusted TIR in quarter *q* and the adjusted TIR in the same quarter of the previous year (*q*-4), scaled by the absolute value of the previous year's adjusted TIR:

$$DAR_{i,q} = \frac{AR_{i,q} - AR_{i,q-4}}{|AR_{i,q-4}|} \qquad (3)$$

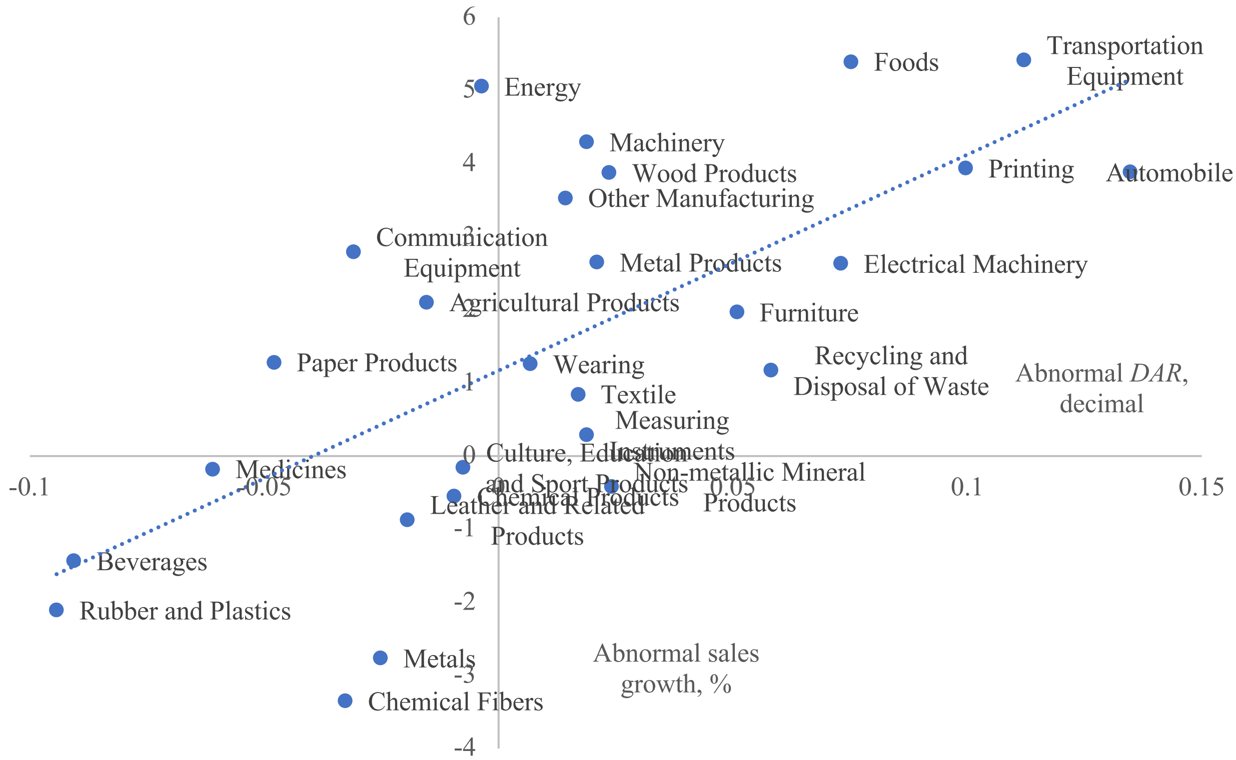
The two variations of the year-over-year change, corresponding to equally weighted and investment-weighted approaches, are denoted as $DARe_{i,q}$ and $DARw_{i,q}$, respectively.

Figure OA.2. Abnormal TIR and sales growth



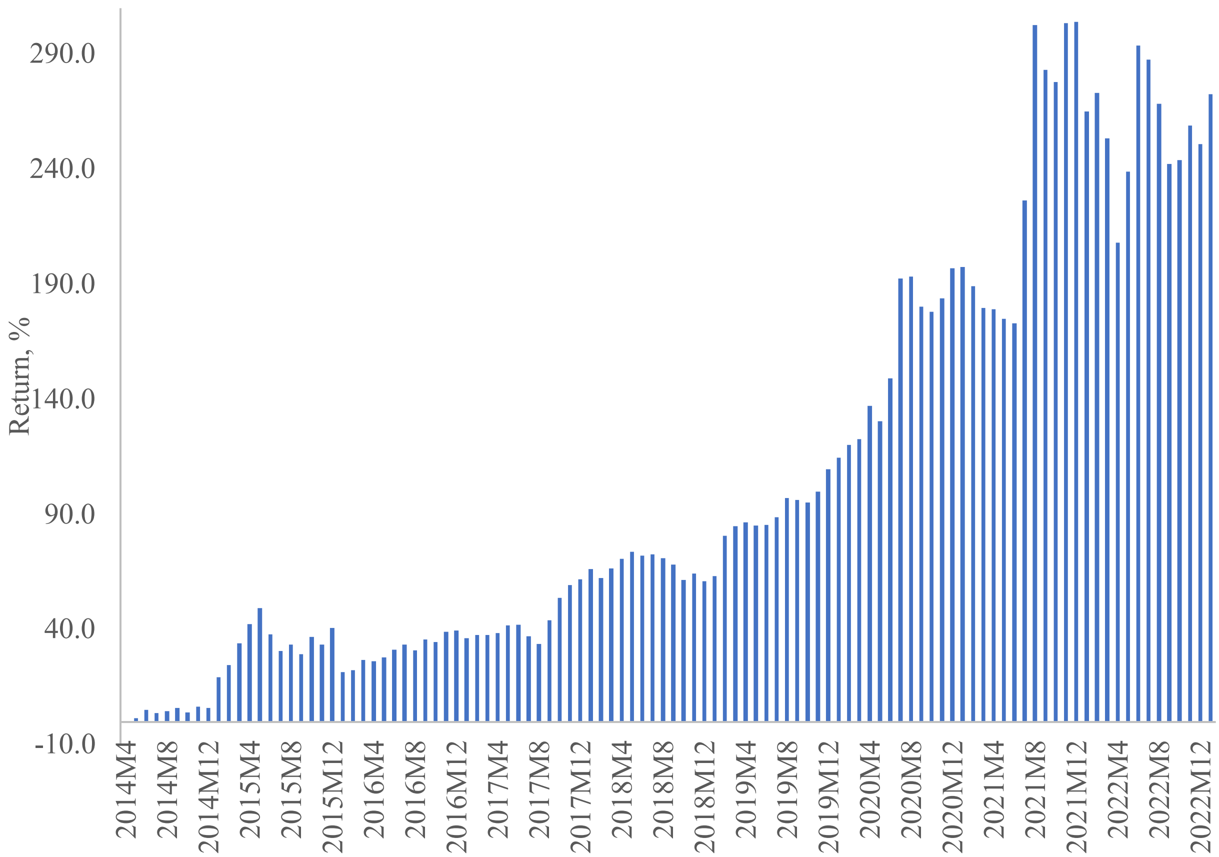
Notes: This figure presents the average abnormal *DAR* and sales growth over time. Abnormal *DAR* is the residual obtained from regressing $DARw_{i,q}$, which is the year-over-year change in the investment-weighted average of adjusted TIR across all factories of firm *i* in quarter *q*, on the firm and regional control variables and firm and year-quarter fixed effects, as specified in Model (5). Similarly, abnormal sales growth is the residual obtained from regressing $SG_{i,q+1}$, which is total sales in quarter $q+1$ minus total sales in quarter $q–3$ (the same quarter of the previous year), scaled by total sales in quarter $q–3$, on the firm and regional control variables and firm and year-quarter fixed effects, as specified in Model (5). The solid line represents the quarterly average of abnormal *DAR*. The dashed line represents the quarterly average of abnormal sales growth.

Figure OA.3. Abnormal TIR and sales growth by industry



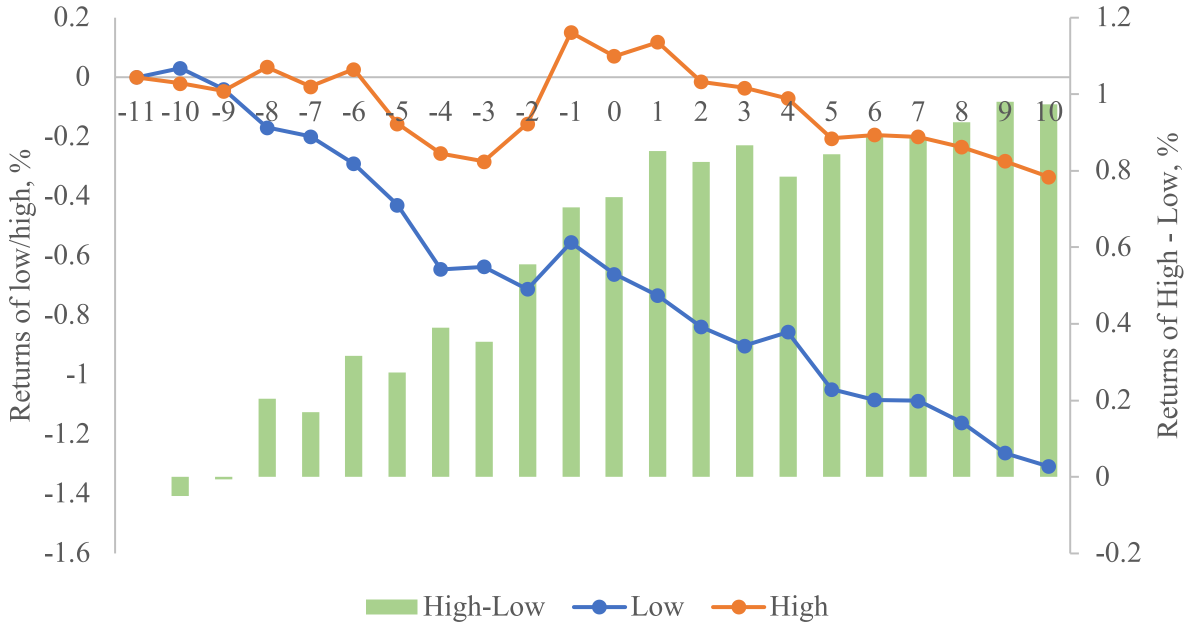
Notes: This figure presents the plot of abnormal *DAR* and sales growth by industry. Abnormal *DAR* is the residual obtained from regressing $DARw_{i,q}$, which is the year-over-year change in the investment-weighted average of adjusted TIR across all factories of firm *i* in quarter *q*, on the firm and regional control variables, as specified in Model (5). The model is run for each year. Industry fixed effects are also included in the regressions. Similarly, abnormal sales growth is the residual obtained from regressing $SG_{i,q+1}$, which is total sales in quarter $q+1$ minus total sales in quarter $q–3$ (the same quarter of the previous year), scaled by total sales in quarter $q–3$, on the firm and regional control variables. Each dot represents the average of abnormal *DAR* and sales growth. The dashed line is the linear regression line that fits all of the dots.

Figure OA.4. Cumulative returns on a hedge portfolio based on TIR



Notes: This figure shows the cumulative returns on a zero-cost hedge portfolio based on corporate TIR. Specifically, for each month *m* from 2014Q2 to 2022Q4, we sort our sample stocks into quintile portfolios based on $DARw_{i,m}$, which is the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm, constructed over the past three months or quarter. We then create a zero-cost hedge portfolio that buys stocks in the top quintile of $DARw_{i,m}$ and sells stocks in the bottom quintile, and calculate this hedge portfolio's value-weighted returns in each month. We finally compute the hedge portfolio's buy-and-hold cumulative returns over our sample period.

Figure OA.5. Earnings announcement returns for firms with high and low TIR



Notes: This figure shows the CAR computed based on the CAPM around firms' EA in quarter *q+1* by portfolios formed by $DARw_{i,q}$, which is the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter *q*. "High" and "Low" indicate the returns of portfolio with stocks in the top and bottom quintiles of $DARw_{i,q}$, respectively. "High – Low" indicates the returns of portfolios that buy the stocks in the top quintile and sell stocks in the bottom quintile.

Table OA.1. Variable definitions and sources

Variable	Definition	Source
Outcome variables:		
$SG_{i,q}$	Total sales in quarter q minus total sales in quarter q–4 (the same quarter of the previous year) scaled by total sales in quarter q–4.	CSMAR
$COGS_{i,q}$	The total costs of goods sold in quarter q minus the total costs of goods sold in quarter q–4 (the same quarter of the previous year) scaled by the total costs of goods sold in quarter q–4.	CSMAR
$Capx_{i,q}$	Cash paid to acquire and construct fixed assets and other long-term assets divided by total assets in quarter q.	CSMAR
$Employment_{i,y}$	The total number of employees in year y minus the total number of employees in year y–1 scaled by the total number of employees in year y–1.	CSMAR
$OperatingMargin_{i,q}$	Operating income divided by total sales in quarter q.	CSMAR
$Ret_{i,q}$	The raw stock return of firm i in quarter q.	CSMAR
$ARet_{i,q}$	Raw returns minus the returns of the corresponding 5 × 5 market value and book-to-market (Size/BM) matched portfolio for firm i in quarter q.	CSMAR
$CAR(-1, 1)_{i, q}$	The three-day CAR, which is computed based on the CAPM, around the EA (day 0) of firm i in quarter q.	CSMAR
$DSHO_{i,q}$	The average daily net short position ((short interest opened – short interest closed) / total trading volume) of firm i in quarter q minus the average daily net short position in quarter q–4, multiplied by 1,000.	CSMAR
$DIO_{i,q}$	The percentage of shares held by the institutional investors of firm i in quarter q minus the percentage of shares held by the institutional investors of firm i in quarter q–4.	CSMAR
TIR variables:		
$AR_{f,q}$	The adjusted TIR for factory f in quarter q, which is the TIR of the factory area minus the TIR of bare lands in the buffer area (see Equation (1)).	Landsat 8/9
$DAR_{f,q}$	The year-over-year change in adjusted TIR for factory f in quarter q, computed using Equation (3).	Landsat 8/9
$DAR_{i,q}$	The year-over-year change in the firm's adjusted TIR across all factories of firm i in quarter q, computed using Equations (2) and (3). It has two variations, $DARe_{i,q}$ and $DARw_{i,q}$.	Landsat 8/9
$DARe_{i,q}$	The year-over-year change in the equally weighted average of adjusted TIR across all factories of firm i in quarter q, computed using Equations (2) and (3).	Landsat 8/9
$DARw_{i,q}$	The year-over-year change in the investment-weighted average of adjusted TIR across all factories of firm i in quarter q, which is computed using Equations (2) and (3).	Landsat 8/9
$DAReL8_{i,q}$	The year-over-year change in the equally weighted average of adjusted TIR developed based on the satellite images of Landsat 8 across all factories of firm i in quarter q, computed using Equations (2) and (3).	Landsat 8
$DARwL8_{i,q}$	The year-over-year change in the investment-weighted average of adjusted TIR developed based on the satellite images of Landsat 8	Landsat 8

	across all factories of firm i in quarter q, computed using Equations (2) and (3).	
$DAReT1_{i,q}$	The year-over-year change in the equally weighted average of adjusted TIR developed based on Tier 1 satellite images across all factories of firm i in quarter q, computed using Equations (2) and (3).	Landsat 8/9
$DARwT1_{i,q}$	The year-over-year change in the investment-weighted average of adjusted TIR developed based on Tier 1 satellite images across all factories of firm i in quarter q, computed using Equations (2) and (3).	Landsat 8/9
$DAReS_{i,q}$	The year-over-year change in the equally weighted average of adjusted TIR across firm *i's* plants of subsidiaries in quarter q, computed using Equations (2) and (3).	Landsat 8/9
$DARwS_{i,q}$	The year-over-year change in the investment-weighted average of adjusted TIR across firm *i's* plants of subsidiaries in quarter q, computed using Equations (2) and (3).	Landsat 8/9
$DAReH_{i,q}$	The year-over-year change in the adjusted TIR of firm *i's* headquarters plant in quarter q, which is computed using Equation (2).	Landsat 8/9
$DAReO_{i,q}$	The change in the equally weighted average of adjusted TIR across firm *i's* office buildings in quarter q, computed using Equations (2) and (3).	Landsat 8/9
$DARwO_{i,q}$	The year-over-year change in the investment-weighted average of adjusted TIR across firm *i's* office buildings in quarter q, computed using Equations (2) and (3).	Landsat 8/9
$DAReM_{i,q}$	The year-over-year change in the equally weighted average of adjusted TIR developed based on the satellite images of MODIS across all factories of firm i in quarter q, computed using Equations (2) and (3).	MODIS
$DARwM_{i,q}$	The year-over-year change in the investment-weighted average of adjusted TIR developed based on the satellite images of MODIS across all factories of firm i in quarter q, computed using Equations (2) and (3).	MODIS
Control variables:		
$Size_{i,q}$	The natural logarithm of the total market value of firm i at the end of quarter q.	CSMAR
$Leverage_{i,q}$	The ratio of long-term debt to total assets.	CSMAR
$Loss_{i,q}$	1 if firm i in quarter q has a negative net profit, and 0 otherwise.	CSMAR
$BM_{i,q}$	The ratio of the book value of total equity to the market value of equity for firm i in quarter q.	CSMAR
$Tangibility_{i,q}$	Fixed assets divided by total assets for firm i in quarter q.	CSMAR
$Plants_{i,q}$	The number of plants of firm i in quarter q.	CNRDS
$Temperature_{i,q}$	The average daily temperature of the cities where firm i's factories are located in quarter q.	CSMAR
$Humidity_{i,q}$	The average daily relative humidity of the cities where firm i's factories are located in quarter q.	CSMAR
$Precipitation_{i,q}$	The average daily precipitation of the cities where firm i's factories are located in quarter q.	CSMAR

$Sunshine_{i,q}$	The average daily sunshine hours of the cities where firm *i*'s factories are located in quarter *q*.	CSMAR
$GDPGrowth_{i,q}$	The average GDP growth rate of the cities where firm *i*'s factories are located in the year of quarter *q*.	CSMAR
$GDP/Capita_{i,q}$	The average GDP per capita of the cities where firm *i*'s factories are located in the year of quarter *q*.	CSMAR
Additional variables:		
$COVID19_{f,q}$	The natural logarithm of 1 plus the number of new COVID-19 infections in factory *f*'s location city in quarter *q*.	National Health Commission
$Energy_{i,q}$	1 if the energy efficiency for the industry of firm *i* in quarter *q* is in the top decile, and 0 otherwise. Energy efficiency is defined as the total sales of the industry to which firm *i* belongs scaled by the total energy consumption of the industry.	China Energy Statistical Yearbook
$TFP_{i,q}$	1 if firm *i*'s TFP calculated based on the Levinsohn and Petrin (2003) (LP) method in quarter *q* is in the top decile, and 0 otherwise.	CSMAR
$SOE_{i,q}$	1 if firm *i* is ultimately owned by the state government in quarter *q*, and 0 otherwise.	CSMAR
$SiteVisit_{i,q}$	1 if the number of financial institutions that conduct corporate site visits to firm *i* in quarter *q* is in the top decile, and 0 otherwise.	CSMAR
$HSR_{i,q}$	1 if the average distance from each plant to the nearest high-speed rail station of firm *i* in quarter *q* is in the top decile, and 0 otherwise.	CSMAR
$EM_{i,q}$	1 if the level of earnings management of firm *i* in quarter *q* is in the top decile, and 0 otherwise, where earnings management is the absolute value of the residuals from regressing firms' total accruals (i.e., the change in current assets minus the change in cash holding minus the change in current liabilities plus the change in short-term debt plus depreciation, scaled by total assets) on the reciprocal of total assets; the change in sales/total assets; and net property, plant, and equipment/total assets (see Kothari et al., 2005).	CSMAR

Table OA.2. The dynamic relationship between TIR and sales growth (without controls)

Panel A. Equally weighted TIR

Dependent variable	$SG_{i,q-1}$	$SG_{i,q}$	$SG_{i,q+1}$	$SG_{i,q+2}$	$SG_{i,q+3}$	$SG_{i,q+4}$	$SG_{i,q+5}$	$SG_{i,q+6}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$DARe_{i,q}$	-0.057	0.024	**0.292****	**0.274***	**0.296***	0.192	-0.014	-0.022
	(0.13)	(0.09)	**(0.12)**	**(0.14)**	**(0.15)**	(0.16)	(0.13)	(0.16)
Control	No	No	No	No	No	No	No	No
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,252	61,239	61,346	60,908	58,257	55,734	53,399	50,995
R-squared	0.182	0.184	0.185	0.191	0.199	0.207	0.216	0.223

Panel B. Investment-weighted TIR

Dependent variable	$SG_{i,q-1}$	$SG_{i,q}$	$SG_{i,q+1}$	$SG_{i,q+2}$	$SG_{i,q+3}$	$SG_{i,q+4}$	$SG_{i,q+5}$	$SG_{i,q+6}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$DARw_{i,q}$	-0.055	0.144	**0.272****	**0.298****	**0.256***	0.103	-0.053	-0.062
	(0.11)	(0.12)	**(0.12)**	**(0.14)**	**(0.13)**	(0.15)	(0.12)	(0.15)
Control	No	No	No	No	No	No	No	No
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,252	61,239	61,346	60,908	58,257	55,734	53,399	50,995
R-squared	0.182	0.184	0.185	0.191	0.199	0.207	0.216	0.223

Notes: The table reports the estimates for the dynamic relationship between corporate TIR and sales growth without including firm and regional characteristic controls. The unit of observation is firm i in a given year-quarter q. The estimation window is 2014Q2–2022Q4. The dependent variable is a firm's sales growth in quarter $q+n$ ($SG_{i,q+n}$, n = –1, 0, 1, 2, 3, 4, 5, and 6). The TIR measures are the year-over-year change in the equally weighted average of adjusted TIR across all factories of a firm in quarter q ($DARe_{i,q}$) (Panel A) and the year-over-year change in investment-weighted average of adjusted TIR across all factories of a firm in quarter q ($DARw_{i,q}$) (Panel B). Variable definitions and data sources are provided in Table OA.1. The standard deviations, shown in parentheses, are estimated with clustering at both the firm and year-quarter levels. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table OA.3. Robustness

$DAR_{i,q}$ in our baseline analysis is constructed by aggregating factory-level TIR, derived from Tier 1 and Tier 2 images from Landsat 8 and 9, across all of a firm's factory plants. This approach is intended to increase sample coverage and generalize the measurement. In this appendix, we use alternative methods to construct the measure and explore the robustness of our results.

1. Landsat 8 images only

We obtain an observation for a specific location approximately every 8 days with the Landsat 8 and 9 satellites, compared with roughly every 16 days before the launch of Landsat 9. Although the two satellites are virtually identical, the differing frequencies of observations in constructing $DAR_{i,q}$ may impact measurement accuracy and, consequently, our estimates. To address this issue, we construct the equally weighted TIR $DAReL8_{i,q}$ and the investment-weighted TIR $DARwL8_{i,q}$ using only data from Landsat 8. We re-estimate Model (5) with these two variables.

The results, presented in Panel A of this appendix, indicate that the coefficients on $DAReL8_{i,q}$ and $DARwL8_{i,q}$ are positive and significant. However, their magnitude is smaller than the corresponding coefficients in Table 3. This implies that while increased observation frequency may enhance measurement accuracy, TIR still retains significant predictive power regarding firms' operating performance even when measured with less frequent observations.

2. Tier 1 images only

We construct corporate TIR using both Tier 1 and Tier 2 Landsat images. While both tiers adhere to the same radiometric standards, Tier 1 images are considered to have higher data quality than Tier 2. Although Tier 2 images constitute only 2.2% of the total images used, their inclusion could potentially introduce noise into our measurements and affect our estimates. We therefore repeat our analysis by creating the equally weighted TIR $DAReT1_{i,q}$ and the investment-weighted TIR $DARwT1_{i,q}$ constructed exclusively with Tier 1 images.

The results, reported in Panel B, show that the coefficients on $DAReT1_{i,q}$ and $DARwT1_{i,q}$ are statistically significant. Their magnitude increases, but non-significantly, compared with the corresponding coefficients reported in Table 3. These findings suggest that exclusion of Tier 2 images may improve the measurement but has a limited impact on our estimates.

3. Plants in headquarters or non-headquarters locations

A firm's key decisions are usually made at its headquarters, while its production and operations are often concentrated in locations away from the headquarters, such as in the suburbs of the headquarters city or in other cities further inland. To test this conjecture, we separate the plants located in the headquarters from those in non-headquarters locations and construct separate TIR measures for the headquarters ($DAReH_{i,q}$) and non-headquarters using both equally weighted TIR ($DAReS_{i,q}$) and investment-weighted TIR ($DARwS_{i,q}$). We then re-estimate the baseline model with these variables.

The results, presented in Panel C, align with our expectations. We observe that the coefficients on TIR at non-headquarters locations for both $DAReS_{i,q}$ and $DARwS_{i,q}$ are positive and significant, while the coefficient for TIR at the headquarters ($DAReH_{i,q}$) is not statistically distinguishable from 0. These findings suggest that the relevance of TIR primarily stems from activities at non-headquarters factories.

4. Office building

Our TIR measure focuses on factories of manufacturing companies, as their operations consume large amounts of energy and emit substantial TIR. As a placebo test, we consider facilities classified as office buildings and examine whether TIR exclusively constructed based on office buildings also has predictive power regarding firms' performance. We construct both the equally weighted average of the change in adjusted TIR across a firm's office buildings in a quarter ($DAReO_{i,q}$) and the investment-weighted average of this change ($DARwO_{i,q}$). We then re-estimate Model (5) using these two variables.

The results, reported in Panel D, show that the coefficients on $DAReO_{i,q}$ and $DARwO_{i,q}$ are positive. However, they are not statistically significant, suggesting that TIR derived from office buildings has limited explanatory power concerning firms' sales performance. This outcome is anticipated, as TIR emitted by administrative activities is weaker and more challenging to detect. Furthermore, multiple firms may occupy the same office building, leading to potential noise in the TIR measurements.

5. MODIS satellite images

Besides the Landsat system, another satellite instrument that gauges land surface TIR is MODIS, which is also operated by NASA. There is a trade-off between spatial and temporal resolution when designing satellites. MODIS has a spatial resolution of 1 km, lower than Landsat's 30 meters. However, MODIS produces daily images, which are more frequent than those of Landsat. Huang *et al.* (2024) use MODIS images to construct TIR at the city level and find that it is positively related to the city's GDP. In this sub-section, we alternatively construct corporate TIR based on MODIS images and examine whether the loss of spatial resolution is offset by the gain in temporal resolution. To do this, we follow the same method and create both the equally weighted average and the investment-weighted average of the change in adjusted TIR across a firm's factories in a quarter ($DAReM_{i,q}$ and $DARwM_{i,q}$, respectively). We then re-estimate Model (5) using these variables.

The results, reported in Panel E, show that the coefficients on both variables are positive and significant. One-standard-deviation increases in $DAReM_{i,q}$ and $DARwM_{i,q}$ are associated with 0.61% (1.19 × 0.51) and 0.50% (1.25 × 0.40) increases in $SG_{i,q+1}$, respectively. The magnitudes of these increases are similar to that for the corresponding measure constructed based on Landsat. This indicates that high-frequency images, despite their coarser spatial resolution, are useful in constructing corporate TIR to gauge firms' operating performance.

6. Remove the pandemic period

The rapid contraction and expansion of the economy during and after the COVID-19 outbreaks raises concerns that our results may be driven by extreme values in changes of TIR and sales growth during this period. To address this concern, we repeat the analysis by excluding observations after 2019. We find that the relationship between $DARe_{i,q}$ and $SG_{i,q+1}$, as well as the relationship between $DARw_{i,q}$ and $SG_{i,q+1}$, remains positive, significant at the 1% level. This suggests that our results are not driven by extreme values and that the relationship between corporate TIR and operating activities holds true even during normal economic periods.

Panel A. Landsat 8 images only

Dependent variable	$SG_{i,q+1}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DAReL8_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARwL8_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**0.260****	**0.279****	**0.253****	**0.261****
	(0.12)	**(0.11)**	**(0.11)**	**(0.11)**
Control	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	61,175	61,175	61,175	61,175
R-squared	0.185	0.202	0.185	0.202

Panel B. Tier 1 images only

Dependent variable	$SG_{i,q+1}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DAReT1_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARwT1_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**0.303****	**0.327****	**0.286****	**0.295****
	(0.14)	**(0.13)**	**(0.12)**	**(0.11)**
Control	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	61,232	61,232	61,232	61,232
R-squared	0.185	0.202	0.185	0.202

Panel C. Plants in headquarters vs. non-headquarters

Dependent variable	$SG_{i,q+1}$					
	Non-headquarters plants				Headquarters	
TIR variable	Equally weighted TIR $DAR_{i,q} = DAReS_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARwS_{i,q}$		$DAR_{i,q} = DAReH_{i,q}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$DAR_{i,q}$	**0.277****	**0.286****	**0.285*****	**0.283*****	**-0.036**	**-0.020**
	(0.11)	**(0.11)**	**(0.10)**	**(0.09)**	**(0.10)**	**(0.10)**
Control	No	Yes	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,957	56,957	56,957	56,957	55,282	55,282
R-squared	0.187	0.206	0.187	0.206	0.185	0.202

Panel D. Office buildings

Dependent variable	$SG_{i,q+1}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DAReO_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARwO_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**0.056**	**0.060**	**0.071**	**0.068**
	(0.07)	**(0.08)**	**(0.09)**	**(0.10)**

Control	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	51,231	51,231	51,231	51,231
R-squared	0.192	0.210	0.192	0.210

Panel E. MODIS satellite images

Dependent variable	$SG_{i,q+1}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DAReM_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARwM_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**0.536****	**0.508****	**0.440****	**0.404***
	(0.23)	**(0.20)**	**(0.21)**	**(0.21)**
Control	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	61,190	61,190	61,190	61,190
R-squared	0.185	0.203	0.185	0.203

Notes: The table reports the estimates for the relationship between corporate TIR and sales growth under alternative specifications. The unit of observation is firm i in a given year-quarter q. The estimation window is 2014Q2–2022Q4. The dependent variable is a firm's sales growth in quarter $q+1$ ($SG_{i,q+1}$). In Panel A, TIR is constructed based on the Landsat 8 satellite images, which include the year-over-year change in the equally weighted average of adjusted TIR across all factories of a firm in quarter q ($DAReL8_{i,q}$) and the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter q ($DARwL8_{i,q}$). In Panel B, TIR is constructed based on the Landsat 8/9 Tier 1 satellite images, which include the year-over-year change in the equally weighted average of adjusted TIR across all factories of a firm in quarter q ($DAReT1_{i,q}$) and the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter q ($DARwT1_{i,q}$). In Panel C, the TIR measures are the year-over-year change in the equally weighted average of adjusted TIR across a firm's plants of subsidiaries in quarter q ($DAReS_{i,q}$), the year-over-year change in the investment-weighted average of adjusted TIR across a firm's plants of subsidiaries in quarter q ($DARwS_{i,q}$), and the year-over-year change in adjusted TIR for a firm's headquarters plant ($DAReH_{i,q}$). In Panel D, the TIR measures are the year-over-year change in the equally weighted average of adjusted TIR across a firm's office buildings in quarter q ($DAReO_{i,q}$) and the year-over-year change in the investment-weighted average of adjusted TIR across a firm's office buildings in quarter q ($DARwO_{i,q}$). In Panel E, TIR is constructed based on the satellite images of MODIS, which include the year-over-year change in the equally weighted average of adjusted TIR across all factories of a firm in quarter q ($DAReM_{i,q}$) and the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter q ($DARwM_{i,q}$). The control variables are the stock return ($Ret_{i,q}$), firm size ($Size_{i,q}$), financial leverage ($Leverage_{i,q}$), profit status ($Loss_{i,q}$), firm valuation ($BM_{i,q}$), asset tangibility ($Tangibility_{i,q}$), number of plants ($Plants_{i,q}$), temperature ($Temperature_{i,q}$), relative humidity ($Humidity_{i,q}$), precipitation ($Precipitation_{i,q}$), sunshine hours ($Sunshine_{i,q}$), GDP growth ($GDPGrowth_{i,q}$), and GDP per capita ($GDP/Capita_{i,q}$). Variable definitions and data sources are provided in Table OA.1. The standard deviations, shown in parentheses, are estimated with clustering at both the firm and year-quarter levels. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table OA.4. TIR and changes in QFII shareholding

Dependent variable	$DQFII_{i,q}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DARe_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARw_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**-0.000**	**-0.000**	**-0.000**	**0.000**
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**
$Ret_{i,q}$		0.001***		0.001***
		(0.00)		(0.00)
$Size_{i,q}$		-0.008		-0.008
		(0.01)		(0.01)
$Leverage_{i,q}$		-0.014		-0.014
		(0.02)		(0.02)
$Loss_{i,q}$		0.001		0.001
		(0.01)		(0.01)
$BM_{i,q}$		-0.014		-0.014
		(0.01)		(0.01)
$Tangibility_{i,q}$		0.031		0.031
		(0.03)		(0.03)
$Plants_{i,q}$		-0.000		-0.000
		(0.00)		(0.00)
$Temperature_{i,q}$		-0.001		-0.001
		(0.00)		(0.00)
$Humidity_{i,q}$		-0.000		-0.000
		(0.00)		(0.00)
$Precipitation_{i,q}$		-0.002		-0.002
		(0.00)		(0.00)
$Sunshine_{i,q}$		-0.003		-0.003
		(0.00)		(0.00)
$GDPGrowth_{i,q}$		-0.000		-0.000
		(0.00)		(0.00)
$GDPPerCapita_{i,q}$		0.000		0.000
		(0.00)		(0.00)
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	61,346	61,346	61,346	61,346
R-squared	0.064	0.148	0.064	0.148

Notes: The table reports the estimates for the relationship between TIR and the trading activities of qualified foreign institutional investors (QFII). The unit of observation is firm i in a given year-quarter q. The estimation window is 2014Q2–2022Q4. The dependent variable is $DQFII_{i,q}$, defined as the change in QFII ownership from quarter q–4 to quarter q. The TIR measures are the year-over-year change in the equally weighted average of adjusted TIR across all factories of a firm in quarter q ($DARe_{i,q}$) and the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter q ($DARw_{i,q}$). The control variables are the stock return ($Ret_{i,q}$), firm size ($Size_{i,q}$), financial leverage ($Leverage_{i,q}$), profit status ($Loss_{i,q}$), firm valuation ($BM_{i,q}$), asset tangibility ($Tangibility_{i,q}$), number of plants ($Plants_{i,q}$), temperature ($Temperature_{i,q}$), relative humidity ($Humidity_{i,q}$), precipitation ($Precipitation_{i,q}$), sunshine hours ($Sunshine_{i,q}$), GDP growth ($GDPGrowth_{i,q}$), and GDP per capita ($GDP/Capita_{i,q}$). Variable definitions and data sources are provided in Table OA.1. The standard deviations, shown in parentheses, are estimated with clustering at both the firm and year-quarter levels. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table OA.5. TIR and A–B share price differences

Panel A. A-B price difference

Dependent variable	*A-B PriceDif$_{i,q}$*			
TIR variable	Equally weighted TIR $DAR_{i,q} = DARe_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARw_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**0.076**	**0.080**	**0.063**	**0.049**
	(0.10)	**(0.11)**	**(0.09)**	**(0.10)**
$Ret_{i,q}$		0.029*		0.029*
		(0.01)		(0.02)
$Size_{i,q}$		2.091		2.085
		(1.70)		(1.70)
$Leverage_{i,q}$		23.139**		23.141**
		(9.00)		(9.00)
$Loss_{i,q}$		0.637		0.625
		(1.06)		(1.05)
$BM_{i,q}$		-1.399		-1.400
		(1.15)		(1.15)
$Tangibility_{i,q}$		18.286		18.323
		(12.41)		(12.42)
$Plants_{i,q}$		0.065		0.065
		(0.05)		(0.05)
$Temperature_{i,q}$		0.074		0.074
		(0.20)		(0.20)
$Humidity_{i,q}$		0.062		0.062
		(0.20)		(0.20)
$Precipitation_{i,q}$		-0.133		-0.134
		(0.47)		(0.47)
$Sunshine_{i,q}$		-0.172		-0.177
		(1.49)		(1.49)
$GDPGrowth_{i,q}$		0.080		0.081
		(0.13)		(0.13)
$GDPPerCapita_{i,q}$		0.381		0.379
		(0.46)		(0.46)
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	1,397	1,397	1,397	1,397
R-squared	0.928	0.933	0.928	0.933

Panel B. Change in A-B price difference

Dependent variable	*Change in A-B PriceDif$_{i,q}$*			
TIR variable	Equally weighted TIR $DAR_{i,q} = DARe_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARw_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**0.135**	**0.098**	**0.104**	**0.052**
	(0.09)	**(0.11)**	**(0.08)**	**(0.10)**
$Ret_{i,q}$		0.056***		0.056***
		(0.02)		(0.02)

$Size_{i,q}$		-1.171		-1.179
		(1.13)		(1.13)
$Leverage_{i,q}$		-7.461		-7.458
		(5.40)		(5.41)
$Loss_{i,q}$		0.397		0.381
		(0.77)		(0.76)
$BM_{i,q}$		1.657		1.656
		(1.12)		(1.13)
$Tangibility_{i,q}$		11.322		11.379
		(7.81)		(7.83)
$Plants_{i,q}$		0.043		0.042
		(0.03)		(0.03)
$Temperature_{i,q}$		0.146		0.147
		(0.14)		(0.14)
$Humidity_{i,q}$		0.032		0.031
		(0.18)		(0.18)
$Precipitation_{i,q}$		0.374		0.372
		(0.41)		(0.41)
$Sunshine_{i,q}$		0.734		0.729
		(1.17)		(1.17)
$GDPGrowth_{i,q}$		-0.010		-0.009
		(0.09)		(0.09)
$GDPPerCapita_{i,q}$		0.239		0.236
		(0.26)		(0.26)
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	1,397	1,397	1,397	1,397
R-squared	0.302	0.324	0.301	0.324

Notes: This table presents regression results examining the relationship between TIR and the A–B share price difference. The unit of observation is firm *i* in a given year-quarter *q*. The sample includes firms with both A and B shares listed on China's two stock exchanges from 2014Q2 to 2022Q4. Panel A reports results where the dependent variable is the level of the A–B share price difference ($A\text{-}B\ PriceDif_{i,q}$), defined as the B-share price minus the A-share price of the same firm, scaled by the A-share price. Panel B uses the change in A–B price difference ($Change\ in\ A\text{-}B\ PriceDif_{i,q,}$) calculated as the difference between the current and lagged A–B price difference (quarter q minus quarter $q-4$). The TIR measures are the year-over-year change in the equally weighted average of adjusted TIR across all factories of a firm in quarter q ($DARe_{i,q}$) and the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter q ($DARw_{i,q}$). The control variables are the stock return ($Ret_{i,q}$), firm size ($Size_{i,q}$), financial leverage ($Leverage_{i,q}$), profit status ($Loss_{i,q}$), firm valuation ($BM_{i,q}$), asset tangibility ($Tangibility_{i,q}$), number of plants ($Plants_{i,q}$), temperature ($Temperature_{i,q}$), relative humidity ($Humidity_{i,q}$), precipitation ($Precipitation_{i,q}$), sunshine hours ($Sunshine_{i,q}$), GDP growth ($GDPGrowth_{i,q}$), and GDP per capita ($GDP/Capita_{i,q}$). Variable definitions and data sources are provided in Table OA.1. The standard deviations, shown in parentheses, are estimated with clustering at both the firm and year-quarter levels. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table OA.6. TIR and earnings announcement returns

Dependent variable	$CAR(-1,1)_{i,q+1}$			
TIR variable	Equally weighted TIR $DAR_{i,q} = DARe_{i,q}$		Investment-weighted TIR $DAR_{i,q} = DARw_{i,q}$	
	(1)	(2)	(3)	(4)
$DAR_{i,q}$	**0.025***	**0.025***	**0.031****	**0.031****
	(0.01)	**(0.01)**	**(0.01)**	**(0.01)**
$Ret_{i,q}$		-0.005		-0.005
		(0.00)		(0.00)
$Size_{i,q}$		-0.358*		-0.359*
		(0.21)		(0.21)
$Leverage_{i,q}$		-0.007		-0.007
		(0.39)		(0.39)
$Loss_{i,q}$		0.378***		0.378***
		(0.11)		(0.11)
$BM_{i,q}$		-0.017		-0.019
		(0.17)		(0.17)
$Tangibility_{i,q}$		0.089		0.087
		(0.44)		(0.44)
$Plants_{i,q}$		0.005		0.005
		(0.00)		(0.00)
$Temperature_{i,q}$		-0.010		-0.010
		(0.02)		(0.02)
$Humidity_{i,q}$		-0.008		-0.008
		(0.01)		(0.01)
$Precipitation_{i,q}$		0.020		0.020
		(0.03)		(0.03)
$Sunshine_{i,q}$		-0.033		-0.033
		(0.08)		(0.08)
$GDPGrowth_{i,q}$		0.007		0.007
		(0.01)		(0.01)
$GDP/Capita_{i,q}$		0.016		0.016
		(0.02)		(0.02)
Firm fixed effects	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
Observations	45,162	45,162	45,162	45,162
R-squared	0.106	0.108	0.106	0.108

Notes: The table reports the estimates for the relationship between TIR and EA returns. The unit of observation is firm i in a given year-quarter q. The estimation window is 2014Q2–2022Q4. The dependent variable is a firm's three-day CAR computed based on the CAPM around the EA of firm i in quarter $q+1$ ($SG_{i,q+1}$). The TIR measures are the year-over-year change in the equally weighted average of adjusted TIR across all factories of a firm in quarter q ($DARe_{i,q}$) and the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter q ($DARw_{i,q}$). The control variables are the stock return ($Ret_{i,q}$), firm size ($Size_{i,q}$), financial leverage ($Leverage_{i,q}$), profit status ($Loss_{i,q}$), firm valuation ($BM_{i,q}$), asset tangibility ($Tangibility_{i,q}$), number of plants ($Plants_{i,q}$), temperature ($Temperature_{i,q}$), relative humidity ($Humidity_{i,q}$), precipitation ($Precipitation_{i,q}$), sunshine hours ($Sunshine_{i,q}$), GDP growth ($GDPGrowth_{i,q}$), and GDP per capita ($GDP/Capita_{i,q}$). Variable definitions and data sources are provided in Table OA.1. The standard deviations, shown in parentheses, are estimated with clustering at both the firm and year-quarter levels. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table OA.7. The heterogeneity of the return predictability of TIR

Dependent variable	$CAR(-1,1)_{i,q+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{DARw_{i,q} \times SiteVisit_{i,q}}$	**-0.137****	**-0.135****				
	(0.06)	**(0.06)**				
$SiteVisit_{i,q}$	0.069	0.148				
	(0.15)	(0.15)				
$\boldsymbol{DARw_{i,q} \times HSR_{i,q}}$			**0.075***	**0.076****		
			(0.04)	**(0.04)**		
$HSR_{i,q}$			-0.098	-0.097		
			(0.13)	(0.13)		
$\boldsymbol{DARw_{i,q} \times EM_{i,q}}$					**0.101****	**0.103****
					(0.05)	**(0.05)**
$EM_{i,q}$					-0.131	-0.115
					(0.11)	(0.11)
$DARw_{i,q}$	0.043**	0.043**	0.023	0.023	0.019	0.019
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Control	No	Yes	No	Yes	No	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,227	28,227	45,162	45,162	45,153	45,153
R-squared	0.105	0.107	0.106	0.108	0.106	0.108

Notes: The table reports the estimates for the heterogeneity of the relationship between TIR and EA returns. The unit of observation is firm i in a given year-quarter q. The estimation window is 2014Q2–2022Q4. The dependent variable is a firm's three-day CAR computed based on the CAPM around the EA of firm i in quarter $q+1$ ($CAR(-1,1)_{i,q+1}$). The TIR measure is the year-over-year change in the investment-weighted average of adjusted TIR across all factories of a firm in quarter q ($DARw_{i,q}$). $SiteVisit_{i,q}$ takes a value of 1 if the number of financial institutions that conduct corporate site visits to firm i in quarter q is in the top decile, and 0 otherwise. $HSR_{i,q}$ takes a value of 1 if the average distance from each plant to the nearest high-speed rail station of firm i in quarter q is in the top decile, and 0 otherwise. $EM_{i,q}$ takes a value of 1 if the level of earnings management of firm i in quarter q is on the top decile, and 0 otherwise, where earnings management is the absolute value of the residuals from regressing firms' total accruals (i.e., the change in current assets minus the change in cash holding minus the change in current liabilities plus the change in short-term debt plus depreciation scaled by total assets) on the reciprocal of total assets; the change in sales/total assets; and net property, plant, and equipment/total assets (see Kothari et al., 2005). The control variables are the stock return ($Ret_{i,q}$), firm size ($Size_{i,q}$), financial leverage ($Leverage_{i,q}$), profit status ($Loss_{i,q}$), firm valuation ($BM_{i,q}$), asset tangibility ($Tangibility_{i,q}$), number of plants ($Plants_{i,q}$), temperature ($Temperature_{i,q}$), relative humidity ($Humidity_{i,q}$), precipitation ($Precipitation_{i,q}$), sunshine hours ($Sunshine_{i,q}$), GDP growth ($GDPGrowth_{i,q}$), and GDP per capita ($GDP/Capita_{i,q}$). Variable definitions and data sources are provided in Table OA.1. The standard deviations, shown in parentheses, are estimated with clustering at both the firm and year-quarter levels. Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.