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From the Editor

We are delighted to publish the January 2024 issue of *Review of Business*, with three academic papers that explore the issues in bond market, REITs, and the impact of generative AI.

The lead article, "Bond Liquidity and Corporate Cash Holdings" by Sun and Duanmu, looks into the impact of bond liquidity on corporate financial policies. The authors exploit two exogenous bond liquidity shocks—the inception of the Trade Reporting and Compliance Engine (TRACE) and the Lehman bankruptcy filing—as well as the traditional measures of bond illiquidity to establish the causal relation between bond liquidity and corporate cash holdings. With the two shocks, the paper shows that bond illiquidity has a causal positive effect on corporate cash holdings. Further analysis also suggests that bond illiquidity increases the value of cash, and this effect is more pronounced for financially constrained firms. These findings corroborate the view that because bond illiquidity hinders firms' access to the external debt market and hence increases the cost of debt, they maintain larger cash holdings to mitigate underinvestment.

In the second article, "Benchmarking the Financial Performance of Office Real Estate Investment Trusts in COVID-19 Era," Dr. Malhotra and Dr. Malhotra look into the real estate investment community, particularly the performance of office real estate investment trusts (REITs) during the tumultuous period of the COVID-19 pandemic. This paper analyzes the operational efficiency of 20 office REITs from 2018 to 2022, with a particular focus on their adaptability in this challenging landscape brought by the COVID-19 pandemic and resultant surge in vacancy rates and a reduction in rental income. The authors find that the average efficiency score of office REITs declined from 89 percent in 2018 to 87 percent in 2022. Moreover, the number of REITs with a perfect 100 percent efficiency score decreased from 9 to 8 during this period. Through peer analysis, best practices and potential avenues for efficiency improvement within these REITs were identified. This evidence underscores the diminished efficiency in the office real estate market following the onset of the COVID-19 pandemic and empowers investors to discern the varying degrees of efficiency among office REITs and make well-informed investment choices. Additionally, REIT managers can employ the efficiency frontier and peer analysis to benchmark their performance and uncover areas for enhancement.

Mr. Yu and Dr. Qi contribute their work "The Impact of Generative AI on Employment and Labor Productivity" as the third article of this issue. This paper examines the influence of generative artificial intelligence (GAI) on employment and labor productivity within the 100 largest publicly traded U.S. companies. The analysis reveals no indication that exposure to GAI diminishes employment levels. However, the authors observe that companies with higher GAI exposure encounter more enhancements in labor productivity, as evidenced by measures such as quarterly real sales per employee, in the nine months following the introduction of ChatGPT. The findings show that the advancement in science and technology, exemplified by GAI, brings benefits to society.

We sincerely hope that scholars and professionals will find this issue of *Review of Business* constructive and enlightening. We will continue to publish high-quality scholarly articles that answer the most imminent questions in the business fields.

Yun Zhu, Editor

Review of Business 44, no. 1, 1–34.

Bond Liquidity and Corporate Cash Holdings

Lingna (Selina) Sun

Jun Duanmu

Abstract

Motivation: This paper is motivated by the fact that asset liquidity is important in asset pricing and has significant implications for corporate investments.

Premise: This paper attempts to fill the gap in the literature by investigating the impact of bond liquidity on corporate financial policies.

Approach: We exploit two exogenous bond liquidity shocks, namely, the inception of the trade reporting and compliance engine (TRACE) and Lehman bankruptcy filing, as well as the traditional measures of bond illiquidity to establish the causal relation between bond liquidity and corporate cash holdings.

Results: This study demonstrates that bond illiquidity has a causal positive effect on corporate cash holdings. Additional analysis suggests that bond illiquidity increases the value of cash, and this effect is more pronounced for financially constrained firms.

Conlusion: Our findings are consistent with the view that because bond illiquidity hinders firms' access to the external debt market and hence increases the cost of debt, they maintain larger cash holdings to mitigate underinvestment.

Consistency: Our results are of interest to regulators who may formulate rules to regulate bond liquidity and practitioners as they make decisions on corporate liquidity and investments.

Keywords: bond liquidity, cash holdings, value of cash

JEL Classification Codes: G30, G32, G34

INTRODUCTION

Creditor rights are crucial to debt contracting. Prior research on bonds concentrates on the debtholder's monitoring role around debt covenant violation. Chava and Roberts (2008) contend that debtholders use the covenant violation threat to push borrowing firms for advanced payoff of loans, thereby intervening in management. They further show that financial covenant violations deteriorate

Lingna Sun, PhD, Louisiana Tech University, lingnas@latech.edu

Jun Duanmu, PhD, CFA, Seattle University, jduanmu@seattleu.edu

the borrowing firms' capital investments. Nini, Smith, and Sufi (2012) find that creditors play an important role in corporate governance. They find that bond covenant violations lead to more conservative investment policies and more chief executive officer (CEO) turnover. Feldhütter, Hotchkiss, and Karakas (2015) evaluate the value of creditor control by estimating the control right. They find that the value of the premium in bond prices increases as firm credit quality decreases. However, few studies pay attention to the effects of bond illiquidity on corporate policies.

Chen, Lesmond, and Wei (2007) report that bond liquidity is priced in corporate yield spreads, and Dick-Nielsen, Feldhütter, and Lando (2012) find that corporate bond illiquidity dramatically increases after the start of the subprime crisis, suggesting that the external financial environment affects bond liquidity. Overall, asset liquidity is an important factor in asset pricing and has important implications for corporate investments; however, little is known about the impact of bond liquidity on corporate financial policies. This paper attempts to fill this gap.

Cash is an important asset that helps firms fund their growth opportunities. The growing cash reserves of U.S. firms have drawn much attention from researchers. Bates, Kahle, and Stulz (2009) report that the average cash-to-asset ratio of U.S. industrial firms increased from 10.5 percent in 1980 to 23.0 percent in 2006. Prior studies suggest various determinants of corporate cash holdings, including transaction costs (Mulligan 1997), agency problems (Dittmar and Mahrt-Smith 2007; Harford, Mansi, and Maxwell 2008), precautionary motives (Opler, Pinkowitz, and Williamson 1999), and idiosyncratic risk (Campbell, Lettau, Malkiel, and Xu 2001). However, the literature has not yet investigated the relation between bond liquidity and cash holdings. This paper attempts to explore whether and how bond liquidity affects corporate cash holdings and the value of cash.

We hypothesize that a firm increases cash holdings to reduce the refinancing risk arising from the increasing bond illiquidity. On one hand, bond illiquidity makes it hard and costly for a firm to refinance; therefore, larger cash reserves enable a firm to meet its contractual obligations without having to resort to asset liquidation. For instance, Harford, Klasa, and Maxwell (2014) argue that firms with shorter maturity debt hold larger cash reserves to reduce costs if they have difficulty refinancing their debt. In addition, high transaction cost and asymmetric information associated with bond illiquidity can also hinder a firm's access to the external debt market, which can push firms to forgo profitable investment projects. In this context, larger cash holdings allow firms to maintain steady investment programs and avoid underinvestment. These lines of argument suggest a positive relation between bond illiquidity and cash holdings.

Next, we ask whether bond illiquidity increases or diminishes the value of cash. While an increase in cash holdings can provide a buffer against financial constraints, they can also exacerbate agency problems as self-interested managers have discretionary power to deploy internal funds. Harford, Mansi, and Maxwell (2008) find that entrenched managers prefer to stockpile cash hoards but spend excess cash quickly. Furthermore, for firms with severe agency problems, large cash holdings enable managers to invest in value-decreasing projects (e.g., Harford 1999). Therefore, examining the value implication of cash will allow us to uncover a firm's underlying motivation for maintaining larger cash reserves.

To the extent that incremental cash holdings associated with bond illiquidity mitigate underinvestment, they should have a positive effect on shareholder value. If this is true, the value effect of incremental cash holdings will be stronger for firms that are financially constrained because these firms are more likely to suffer from underinvestment (Faulkender and Wang 2006; Denis and Sibilkov 2010). On the other hand, if firms reserve cash simply for precautionary motives due to bond illiquidity, they will incur opportunity costs, implying a negative value effect of bond illiquidity on incremental cash holdings. Given the possible opposing effects of bond liquidity on the value of cash, this paper attempts to sort them out empirically.

This paper starts by investigating how bond illiquidity affects a firm's cash holdings. Specifically, we perform the regressions of cash-to-assets ratio on the bond illiquidity using alternative proxies of bond while controlling for other variables. The bond illiquidity measures include (1) the widely used *Amihud* ratio (Amihud 2002), which is constructed by the bond's daily trading information, (2) the *Roll* (1984) measure, which reflects the effective bid-ask spread from negative serial dependence of consecutive changes of price, (3) the imputed round-trip cost (*IRC*) based on the range of daily bond trade prices, (4) *HL_Spread* measure, which is estimated as the bid-ask spreads for bonds based on high and low prices, and (5) *Gibbs* measure, which is estimated as effective half-spread by using a Bayesian Gibbs sampler (Hasbrouck 2009).

The results show that firms increase cash holdings as bond illiquidity deteriorates. Note that continuous measures of bond illiquidity may raise two endogeneity concerns. First, cash reserves and bond illiquidity can both be determined by certain unobserved variables, such as firm financial health. Second, it is possible that firms anticipate lower bond liquidity and, thus, increase cash holdings as a precautionary measure, implying reverse causality. To mitigate these concerns, two exogenous shocks are employed to bond liquidity using the Lehman bankruptcy filing and the introduction of the trade reporting and compliance engine (TRACE) to establish the causal relation between bond illiquidity and cash holdings. On September 15, 2008, Lehman Brothers, one of the largest dealers in the corporate bond market, filed for bankruptcy protection under Chapter 11. Lehman's collapse meant that most of its security assets were nearly unrecoverable, precipitating a dramatic fall in bond liquidity: Transaction costs roughly tripled shortly after the bankruptcy filing (Nagler 2015).

If an adverse exogenous shock to bond illiquidity leads to an increase in cash holdings, a positive shock to bond illiquidity is expected to lead to a decrease in cash holdings. Therefore, we additionally exploit the positive shock to bond illiquidity arising from the introduction of TRACE to examine this proposition. In July 2002, the National Association of Securities Dealers (NASD) introduced TRACE to enhance price transparency in the U.S. corporate debt market. With this new technology platform, bond dealers were required to report all trading information of publicly issued corporate bonds in terms of yield, price, investment grade, and convertible corporate debt, among other items. Previous studies show that the introduction of TRACE lowered bonds' bid-ask spread by approximately 50 percent, implying a significant increase in bond liquidity (Bessembinder and Maxwell 2008; Jankowitsch, Nashikkar, and Subrahmanyam 2011).

Using a sample of 4,208 firm-year observations of 792 unique firms over the period 2002–2012,[1] we find that bond illiquidity is positively associated with corporate cash hoards, suggesting that deteriorated bond liquidity induces firms to hold more cash. These results are robust to the use of traditional measures of bond illiquidity and the shocks to bond liquidity caused by the Lehman bankruptcy filing and the introduction of TRACE for identification purposes. The economic effect of bond illiquidity on corporate cash holdings is important: The estimation reveals that the increase in bond illiquidity due to the Lehman bankruptcy filing increased the cash-to assets ratio of an average firm by 0.012 points, which is equivalent to 0.101 of its sample mean.

Next, we investigate the value implication of bond illiquidity to shareholders by employing the cash value regression of Faulkender and Wang (2006) and Dittmar and Mahrt-Smith (2007). We find that bond illiquidity has a positive and significant effect on the value of cash. Holding other variables unchanged at their sample means, the value of $1 of incremental cash holdings for an average firm is $0.142 higher due to the increase in bond illiquidity caused by the Lehman bankruptcy.

Using an exogenous shock to bond liquidity for identification purposes could raise a concern: The shock may be confounded by other events occurring around the Lehman bankruptcy (the introduction of TRACE) that also affected corporate cash holdings and the value of cash. To alleviate such concerns, we perform falsification tests by rerunning the cash holdings and the value of cash regression in placebo periods. We find no evidence that bond illiquidity affects cash holdings or increases the value of cash during these placebo periods.

If bond illiquidity increases transaction cost and thus hinders a firm's access to the external debt market, the positive value implication of incremental cash holdings should be more pronounced for financially constrained firms. To explore this possibility, the cash value regressions are performed but augment with the three-way interaction of bond illiquidity, incremental cash holdings, and the proxies for financial constraints (e.g., MB ratio, payout ratio, Whited and Wu [2006] index, credit rating status [Faulkender and Petersen 2006], and SA index [Hadlock and Pierce 2010]). Our results support the argument that the value effect of bond illiquidity on the value of cash is stronger for financially constrained firms.

This research contributes to literature in three ways. First, extant studies tend to focus on the impact of stock liquidity on corporate governance and firm policies. Edmans and Manso (2011), Edmans, Fang, and Zur (2013), and Bharath, Jayaraman, and Nagar (2013) argue that stock liquidity improves blockholders' governance effectiveness even without the need for their intervention. Using decimalization as an exogenous shock to stock liquidity, Fang, Noe, and Tice (2009) find that stock liquidity increases firm value as measured by market-to-book ratio. In addition, Fang, Tian, and Tice (2014) suggest that stock liquidity impedes corporate innovation as it heightens the hostile takeover risk and increases the presence of passive institutional holders. However,

[1]We restrict our sample period to 2002–2012 because the Lehman bankruptcy takes place in 2008 and the phase-in program of TRACE occurs between 2002 and 2005. Our untabulated results show that the results of cash holdings and value of cash still hold if we use continuous measures of bond liquidity for the period 2002–2020.

few studies consider how bond illiquidity affects corporate performance. This research provides first-time evidence about the causal relation between bond illiquidity and cash holdings and the value of cash. Second, this paper adds to the literature by suggesting bond illiquidity as another important determinant of cash holdings. Third, this study can be useful for regulators in policy making and corporate managers in making corporate decisions because bond illiquidity can be altered by the enactment of laws and corporate cash holdings are important for corporate liquidity.

The rest of the paper proceeds as follows:

- Data, variables construction, and descriptive statistics
- Empirical models, results, and discussion
- Robustness check
- Conclusion

DATA, VARIABLES CONSTRUCTION, AND DESCRIPTIVE STATISTICS

Data Description

Bond daily trading data from TRACE and accounting data is obtained from Compustat. Financial firms (with four-digit Standard Industry Classification (SIC) codes from 6000 to 6999) and utility firms (with four-digit SIC codes from 4900 to 4999) are excluded from the sample because these firms are more regulated, and their cash holdings have a different implication. In addition, variables are winsorized at the top and bottom 1 percent to mitigate the impact of outliers. The final sample contains 4,208 firm-year observations of 792 unique firms from 2002 to 2012.

To mitigate possible reporting errors in TRACE, in line with Dick-Nielsen, Feldhütter, and Lando (2009), we adopt the following rules to clean the high-frequency trading data of bonds: (1) Duplicates indicated by the message sequence number are deleted, (2) both the original trade and the reversal are excluded if a trade is reversed, (3) corrections in the same day are dropped (if the correction is a cancellation, both reports are excluded; otherwise, the original report is excluded), and (4) a trade with par value below \$100,000 is deleted to exclude retail-sized trades.

Bond Illiquidity Measures

Five continuous measures are used to capture different aspects of bond illiquidity. The first proxy is Amihud's (2002) illiquidity measure, which captures the price impact of trades. The daily Amihud measure is calculated as the average ratio of absolute returns to the trade size of consecutive transactions. A higher Amihud value implies higher bond illiquidity.

$$Amihud_{i,t} = \frac{1}{N_t} \times \sum_{t=1}^{N_t} \frac{\left|\frac{P_{i,j}-P_{i,j-1}}{P_{i,j-1}}\right|}{|Q_{i,d}|} \tag{1}$$

Where

$N_{i,t}$ is the number of trades on day t

$P_{i,j}$ and $P_{i,j-1}$ are the prices for two consecutive trades on day t

$Q_{i,d}$ is the trade size of the d^{th} trade for bond i

The annual Amihud measure is defined as the average of the daily Amihud measures.

The second measure of bond illiquidity is the imputed roundtrip cost. Feldhütter (2012) shows that this measure captures the variation in trade prices around the market-wide valuation.

$$IRC_t = \frac{P_{max}-P_{min}}{P_{max}} \tag{2}$$

Where

P_{max} is the largest price in an imputed IRT

P_{min} is the smallest price in the IRT

If two or three trades in a given bond with the same trade size take place on the same day, and there are no other trades with the same size on that day, they may reflect the trading of a dealer taking one side of the trade and then the opposite side. Therefore, the buy-sell matched trades are defined as imputed roundtrip transactions.

Schestag, Schuster, and Uhrig-Homburg (2016) compare 12 proxies of bond illiquidity measures. The authors find that three proxies take the lead to capture transaction costs: Roll's (1984) measure, Corwin and Schultz's (2012) high-low spread estimator, and Hasbrouck's (2009) Gibbs measure. Therefore, we additionally adopt the following proxies as bond illiquidity.

The third bond illiquidity measure follows Roll (1984) and is measured as two times the square root minus the covariance between consecutive returns. It captures the effective bid-ask spread from the negative serial interdependence of a consecutive price switch:

$$Roll_t = 2\sqrt{-cov(R_i - R_{i-1})} \tag{3}$$

Where

$R_{i,t}$ and $R_{i,t-1}$ are returns to two consecutive trades, computed as price changes scaled by the price of the first trade

cov is the covariance is based on days using a rolling window of 21 trading days

$Roll_t$ is an annual Roll measure defined as the average of the daily measures within the year

The fourth bond illiquidity measure follows Corwin and Schultz (2012) and is estimated as the bid-ask spreads for bonds based on high and low prices.

The authors contend that daily high (low) prices are usually accompanied by buy (sell) trades. Therefore, the high-low ratio implies both the stock's variance and its bid-ask spread. The stock's variance is associated with the return interval, and the bid-ask spread should be constant. This enables the authors to construct a spread estimator as a function of high-low ratios over 1-day and 2-day intervals.

The fifth bond illiquidity measure, Gibbs, follows Hasbrouck (2009) and is estimated as effective half-spread by using a Bayesian Gibbs sampler.[2] Schestag, Schuster, and Uhrig-Homburg (2016) argue that the Gibbs measure can arcuately estimate the transaction costs and perform especially well for retail-sized trades.

Note that the use of continuous measures of bond illiquidity may raise two endogeneity concerns. First, cash reserves and bond illiquidity can be jointly related to unobservable firm characteristics, such as the firm's financial health. Second, while lower bond illiquidity can induce firms to stockpile more cash to buffer against a potential liquidity shortfall, firms can anticipate lower bond illiquidity in the future and increase cash holdings as a precautionary measure, implying that reverse causality is another source of endogeneity. To mitigate these concerns, this paper exploits a negative shock to bond illiquidity using the Lehman bankruptcy filing to identify the causal relation between bond illiquidity and cash holdings. On September 15, 2008, Lehman Brothers, one of the largest dealers in the corporate bond market, filed for bankruptcy protection. Most of its assets were unrecoverable after it failed. Lehman's demise reduced corporate bond illiquidity sharply as bond transaction costs tripled shortly after its bankruptcy filing (Nagler 2015).

We also consider a positive shock to bond liquidity (i.e., introduction of TRACE) to further identify the causal relation between bond illiquidity and cash holdings and the value of cash. To improve bond market trading transparency, members of the Financial Industry Regulatory Authority have been required to report their over-the-counter bond transactions through TRACE starting from January 2001. Due to the uncertainty about the benefits of the disclosure, not all trades were reported to TRACE until July 1, 2002. Reports to TRACE increased gradually and were fully implemented starting in January 2006 (Dick-Nielsen, Feldhütter, and Lando 2012). Prior literature shows that the introduction of TRACE improved information transparency and thus reduced transaction costs (Edwards, Harris, and Piwowar, 2007; Goldstein, Hotchkiss, and Sirri 2007). Therefore, using the phase-in program of TRACE between 2002 and 2005 allows us to identify the relation between bond illiquidity and cash holdings.

Descriptive Statistics

Table 1 reports the summary statistics of the sample. The definitions of the variables are provided in the Appendix. The summary statistics indicate that an average firm holds 12.6 percent of total assets in cash. The distribution of cash holdings is skewed to the right as the median firm holds 7.4 percent of assets in cash. The five measures of bond illiquidity, *Amihud, IRC, Roll, Gibbs,* and *HL_*

[2]The SAS program to generate measure *Gibbs* and data are available from http://people.stern.nyu.edu/jhasbrou/EMM%20Book/SAS%20Programs%20and%20Data/Description.html.

TABLE 1. Summary Statistics

The sample includes 792 unique firms over the period from 2002 to 2012. *Cash/Assets* is the ratio of cash plus marketable securities to total assets. Illiquidity measures *Amihud, IRC, Roll, Gibbs,* and *HL_Spread* are calculated using the models presented in the text. *Acquisition* is the ratio of acquisition value to total assets. *Rate* is the dummy variable, which equals 1 for firms having a credit rating and 0 otherwise. *Coupon* is the coupon rate of the bond for a specific firm. *M/B* is measured as book value of total assets minus book value of common equity plus the market value of equity, divided by book value of total assets. *Capex* is the ratio of capital expenditures to total assets. *Financial leverage* is measured as long-term debt plus debt in current liabilities, divided by total assets. *NWC* is measured as working capital minus cash and marketable securities, divided by total assets. The definitions of other variables are provided in the Appendix. Variables are winsorized at the top and bottom 1 percent to reduce the impact of outliers.

Variable	N	First Quartile	Mean	Median	Third Quartile	SD
Cash/Assets	4,208	0.029	0.126	0.074	0.165	0.139
Amihud	4,208	0.221	1.253	0.629	1.411	0.734
IRC	4,208	0.218	0.527	0.436	1.128	0.358
Roll	4,208	0.821	1.521	1.213	4.062	0.813
Gibbs	4,208	0.542	1.320	1.121	2.087	0.637
HL_Spread	4,208	0.432	1.321	0.832	1.631	0.926
Rate	4,208	1	0.842	1	1	0.015
Coupon	4,208	3.802	5.283	5.229	6.733	1
Industry Sigma	4,208	0.045	0.083	0.07	0.107	0.254
MB	4,208	1.185	1.715	1.473	1.955	0.477
Size	4,208	7.234	8.246	8.139	9.193	1.306
Cash flow/Assets	4,208	0.05	0.072	0.078	0.11	0.698
NWC	4,208	–0.036	0.037	0.027	0.111	0.515
Capex	4,208	0.021	0.057	0.037	0.066	0.315
Financial leverage	4,208	0.2	0.33	0.291	0.418	0.057
R&D/Sales	4,208	0	0.063	0	0.029	0.031
Dividend	4,208	0	0.518	1	1	0.188
Acquisition	4,208	0	0.029	0.002	0.024	0.359

Spread, have means (medians) of 1.253 (0.629), 0.527 (0.436), 1.521 (1.213), 1.320 (1.121), and 1.321 (0.832), respectively. These figures are close to those reported by Schestag, Schuster, and Uhrig-Homburg (2016) and Dick-Nielsen, Feldhütter, and Lando (2012).

EMPIRICAL MODELS, RESULTS, AND DISCUSSION

Bond Illiquidity and Corporate Cash Holdings

To investigate how bond illiquidity affects firms' cash holdings, this paper employs a model of cash holdings similar to Opler, Pinkowitz, and Williamson (1999) and Bates, Kahle, and Stulz (2009) but augments it with a bond illiquidity measure. The model is specified as follows:

$$Cash_{i,t} = \alpha_0 + \beta_1 Illiquidity_{i,t-1} + \beta_2 Industry\ Sigma_{i,t-1} + \beta_3 M/B_{i,t-1} + \beta_4 Size_{i,t-1} + \beta_5 \left(\frac{Cashflow}{Assets}\right)_{i,t-1} + \beta_6 \left(\frac{NWC}{Assets}\right)_{i,t-1} + \beta_7 Capex_{i,t-1} + \beta_8 \left(\frac{R\&D}{Sales}\right)_{i,t-1} + \beta_9 Dividend_{i,t-1} + \beta_{10} Acquisition_{i,t-1} + \beta_{11} Coupon_{i,t-1} + \beta_{12} Rate_{i,t-1} + \varepsilon_{i,t}\ , \quad (4)$$

Where the dependent variable is the ratio of cash to total assets.

The variable of interest is bond illiquidity, which captures the sensitivity of cash holdings to the variation in bond illiquidity. Other control variables include industry cash flow volatility, market-to-book ratio, firm size, cash flows, net working capital, capital expenditures, financial leverage, research and development (R&D), acquisition activities, coupon, and rate. *Coupon* is the coupon rate of the bonds for specific firm. *Rate* is an indicator that equals to one for firms have the credit rating, and zero otherwise. We include the credit ratings because it may affect a firm's bond illiquidity. Prior studies provide mixed evidence of the relation between bond illiquidity and credit risk. For example, Harris and Piwowar (2006) and Edwards, Harris, and Piwowar (2007) find that lower rated bonds have larger transaction costs. Conversely, Bao, Pan, and Wang (2011) and Goldstein and Hotchkiss (2020) find no significant relation between ratings and bond illiquidity. We provide variable definitions in the Appendix. We control industry-/firm- and year fixed effects because these common factors and time-varying macroeconomic conditions can also affect corporate cash holdings. Consistent with the prediction, the coefficient of bond illiquidity, β_1, is expected to be positive.

Table 2 reports the results of the panel regressions with continuous bond illiquidity measures. The results in Panel A and Panel B show that the coefficients of *Amihud, IRC, Roll, Gibbs,* and *HL_Spread* are positive across columns and statistically significant at the 10 percent level or better, which is consistent with the prediction of a positive effect of bond illiquidity on corporate cash holdings. The economic effect of bond illiquidity on corporate cash holdings is nontrivial. Using the results in Panel A to estimate the economic significance, a decrease of one standard deviation in the IRC measure increases the cash-to-assets ratio of an average firm by 0.003, which is equivalent to 2.5 percent of its sample mean. The coefficients of other control variables have signs and significance consistent with those documented in the literature. For instance, the coefficients on M/B are significantly positive, implying that firms with more growth opportunities hold larger cash buffers. While the test results provide some support for the argument that bond illiquidity enhances corporate cash holdings, we refrain from drawing a conclusion here due to the endogeneity concerns discussed in *Bond Illiquidity Measures,* above.

To alleviate the endogeneity concern, the continuous bond illiquidity measures are replaced with a Lehman bankruptcy filing indicator, labeled *Lehman,* to identify the causal relation between bond illiquidity and cash holdings. Furthermore, to mitigate the confounding effects of other possible events that occurred around the year of the Lehman filing for bankruptcy protection (2008), the regression sample includes one year before and one year after the Lehman filing. In particular, *Lehman* is an indicator that takes a value of 1 for the year 2009 and 0 for the year 2007.[3] The test results reported in columns 1 and 2 of Panel A in Table 3 show that the coefficient of *Lehman* is positive and statistically significant at the 1 percent level. The economic effect is also large: The point estimates indicate that, holding other variables unchanged at their sample means, the decline in bond illiquidity associated with the Lehman bankruptcy

[3]Our results still hold if we expand our sample period to 2006–2008.

(text continues on page 12)

TABLE 2. Bond Illiquidity and Cash Holdings

This table reports the regressions of cash holdings on five continuous bond illiquidity measures. Illiquidity measures *Amihud*, *IRC*, *Roll*, *Gibbs*, and *HL_Spread* are calculated using the models displayed in the text. Panel A reports the results controlling for industry- and year-fixed effects. Panel B reports the results controlling for firm- and year-fixed effects. Other variables are defined in the Appendix. The models are estimated with year and firm fixed effects. The *t*-statistics reported in parentheses are based on heteroskedasticity-robust standard errors clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: OLS Regressions Controlling for Industry Fixed Effects

	(1)	(2)	(3)	(4)	(5)
$Amihud_{t-1}$	0.111** (2.23)				
IRC_{t-1}		0.006** (2.11)			
$Roll_{t-1}$			0.109** (2.19)		
$Gibbs_{t-1}$				0.089* (1.68)	
HL_Spread_{t-1}					0.285* (1.68)
$Coupon_{t-1}$	−0.006*** (3.36)	−0.006*** (7.11)	−0.007*** (3.45)	−0.048*** (3.50)	−0.014 (1.11)
$Rate_{t-1}$	−0.069*** (5.96)	−0.068*** (13.62)	−0.081*** (6.60)	0.026 (0.69)	0.089* (1.68)
MB_{t-1}	0.035*** (7.56)	0.042*** (14.68)	0.040*** (10.59)	0.025*** (9.44)	0.005 (0.88)
$Cash\ Flow_{t-1}/Assets_{t-1}$	−0.154*** (3.53)	−0.165*** (6.58)	−0.230*** (4.75)	−0.223*** (6.22)	0.045 (0.50)
$Size_{t-1}$	−0.016*** (5.53)	−0.015*** (10.19)	−0.016*** (5.31)	−0.013*** (3.39)	0.015 (0.55)
$NWC_{t-1}/Assets_{t-1}$	−0.221*** (7.07)	−0.217*** (13.29)	−0.270*** (8.17)	−0.667*** (18.83)	−0.414*** (3.11)
$Capex_{t-1}$	−0.443*** (8.84)	−0.454*** (13.24)	−0.436*** (7.69)	−1.031*** (9.94)	−0.667*** (4.11)
Financial $leverage_{t-1}$	−0.079*** (4.14)	−0.075*** (7.51)	−0.095*** (4.39)	−0.491*** (18.21)	−0.191** (2.41)
$Dividend_{t-1}$	−0.029*** (4.80)	−0.029*** (8.02)	−0.034*** (5.13)	−0.086*** (6.81)	−0.029 (0.89)
$R\&D_{t-1}/Sales_{t-1}$	0.155*** (5.28)	0.159*** (16.53)	0.000 (0.01)	0.121*** (18.19)	0.025 (1.04)
$Acquisition_{t-1}$	−0.213*** (9.16)	−0.230*** (9.81)	−0.264*** (10.84)	−0.458*** (5.92)	−0.280*** (2.90)
Industry $Sigma_{t-1}$	0.020 (0.18)	0.013 (0.14)	0.003 (0.03)	2.337*** (4.02)	0.009 (0.02)
Intercept	0.308*** (7.82)	0.255*** (11.13)	0.295*** (7.71)	0.568*** (2.85)	0.285* (1.68)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	4,208	4,208	4,208	4,208	4,208
Adj. R-squared	0.57	0.56	0.56	0.53	0.26

(*continues*)

Panel B: OLS Regressions Controlling for Firm Fixed Effects					
	(1)	(2)	(3)	(4)	(5)
$Amihud_{t-1}$	0.006*** (3.82)				
IRC_{t-1}		0.011** (2.40)			
$Roll_{t-1}$			0.008** (2.09)		
$Gibbs_{t-1}$				0.381** (1.98)	
HL_Spread_{t-1}					0.371* (1.93)
$Coupon_{t-1}$	0.011*** (5.38)	0.046*** (23.43)	0.010*** (4.99)	0.045*** (23.20)	0.010*** (4.99)
$Rate_{t-1}$	0.018 (0.50)	–0.737*** (19.21)	0.013 (0.36)	–0.734*** (19.12)	0.012 (0.34)
MB_{t-1}	0.027*** (10.29)	0.005 (0.88)	0.028*** (10.89)	0.006 (0.95)	0.040*** (13.63)
Cash $Flow_{t-1}/Assets_{t-1}$	–0.253*** (7.13)	0.045 (0.50)	–0.252*** (7.10)	0.044 (0.49)	–0.633*** (10.61)
$Size_{t-1}$	–0.012*** (3.25)	0.015 (0.55)	–0.014*** (3.98)	0.014 (0.50)	–0.033*** (14.66)
$NWC_{t-1}/Assets_{t-1}$	–0.589*** (19.21)	–0.414*** (3.11)	–0.578*** (18.96)	–0.406*** (3.11)	–0.424*** (15.52)
$Capex_{t-1}$	–1.197*** (13.39)	–0.667*** (4.11)	–1.179*** (13.22)	–0.646*** (4.14)	–0.537*** (9.76)
Financial $leverage_{t-1}$	–0.484*** (18.87)	–0.191** (2.41)	–0.486*** (18.96)	–0.179** (2.28)	–0.316*** (15.38)
$Dividend_{t-1}$	–0.082*** (6.85)	–0.029 (0.89)	–0.086*** (7.16)	–0.027 (0.85)	–0.074*** (13.16)
$R\&D_{t-1}/Sales_{t-1}$	0.128*** (20.03)	0.025 (1.04)	0.129*** (20.12)	0.027 (1.10)	0.001** (2.44)
$Acquisition_{t-1}$	–0.471*** (6.16)	–0.280*** (2.90)	–0.464*** (6.06)	–0.273*** (2.84)	–0.301*** (9.87)
Industry $Sigma_{t-1}$	1.428*** (9.90)	0.009 (0.02)	1.361*** (9.53)	–0.216 (0.42)	0.288 (1.48)
Intercept	0.443*** (15.58)	0.011 (0.30)	0.435*** (15.81)	0.313* (1.86)	0.040*** (13.63)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	4,208	4,208	4,208	4,208	4,208
Adj. R-squared	0.45	0.81	0.44	0.81	0.44

filing increases the cash-to-assets ratio of an average firm by 0.012, which is equivalent to 10.1 percent of its sample mean.

To further address the concern that some simultaneous events that occur around the Lehman filing also affect cash holdings, this study additionally conducts falsification tests using placebo periods. Specifically, 2011 is assumed as the counterfactual Lehman bankruptcy filing year. Then a placebo dummy is constructed, which equals 1 for firm-year observations in 2012 and 0 for those in 2010. The results in columns 3 and 4 of Panel A show that the placebo effect on cash holdings is statistically not different from zero.

If the negative shock to bond liquidity increases cash hoards, a positive shock to bond liquidity is expected to reduce corporate cash holdings. Hence, this study employs another exogenous shock, the inception of TRACE, to further examine the relation between bond illiquidity and cash holdings. The phase-in feature of the inception of TRACE allows us to exploit the variation of bond liquidity, which is unlikely to affect cash reserves directly, for test purposes. Specifically, among all COMPUSTAT firms with credit ratings from 2002 to 2005, we create a TRACE dummy, which equals 1 if TRACE reports the daily trading information for a bond of a given firm, and 0 otherwise. The results reported in columns 1 and 2 of Panel B, Table 3 indicate that an increase in bond liquidity leads to a decrease in cash holdings. Again, the falsification tests around the placebo period show little impact of bond illiquidity on cash holdings.

Overall, the results in this section indicate a positive relation between bond illiquidity and corporate cash holdings.[4]

Bond Illiquidity and Corporate Cash Value

We adopt Faulkender and Wang (2006) cash value model that uses excess equity returns to evaluate the marginal value of cash holdings. We augment the model with bond illiquidity and an interaction between bond illiquidity and the change in cash holdings while controlling for other factors documented in the literature to explain excess equity returns. Dittmar and Mahrt-Smith (2007) and Liu and Mauer (2011), among others, use a similar model in their analysis of the value of cash. The cash value model is stated as follows:

$$r_{i,t} - R^B_{i,t} = \gamma_0 + \gamma_1 Liquidity_{i,t-1} + \gamma_2 Liquidity_{i,t-1} \times \frac{\Delta C_{i,t}}{M_{i,t-1}} + \gamma_3 \frac{\Delta C_{i,t}}{M_{i,t-1}} + \gamma_4 \frac{\Delta E_{i,t}}{M_{i,t-1}} + \gamma_5 \frac{\Delta NA_{i,t}}{M_{i,t-1}} + \gamma_6 \frac{\Delta RD_{i,t}}{M_{i,t-1}} + \gamma_7 \frac{\Delta I_{i,t}}{M_{i,t-1}} + \gamma_8 \frac{\Delta D_{i,t}}{M_{i,t-1}} + \gamma_9 \frac{C_{i,t-1}}{M_{i,t-1}} + \gamma_{10} L_{i,t} + \gamma_{11} \frac{NF_{i,t}}{M_{i,t-1}} + \gamma_{12} \frac{C_{i,t}}{M_{i,t-1}} \times \frac{\Delta C_{i,t}}{M_{i,t-1}} + \gamma_{13} Leverage_{i,t} \times \frac{\Delta C_{i,t}}{M_{i,t-1}} + \gamma_{14} Coupon_{i,t-1} + \gamma_{15} Rate_{i,t-1} + \varepsilon_{i,t}, \tag{5}$$

[4]Corporate cash holdings are also associated with managers' risk-taking preference. Liu and Mauer (2011) find that cash holdings are positively related to CEO risk-taking incentives, as measured by Vega. These authors further contend that a stronger appetite for risk motivates CEOs to engage in risky investments that can enhance shareholder value but is potentially harmful to creditors. Consequently, debtholders are likely to demand larger cash reserves from firms to mitigate the increased cost of borrowing. In our research framework, if weak credit rights restrict firms' access to capital markets and thereby increase the cost of borrowing, creditors may request firms to hold more precautionary cash holdings. This suggests that the positive relation between bond illiquidity and corporate cash reserves is more pronounced for firms led by risk-taking managers. We thank an anonymous reviewer for suggestion to discuss the potential impact of manager's risk-taking preference on the relation between bond illiquidity and corporate cash holdings.

(text continues on page 14)

TABLE 3. Lehman Bankruptcy Filing, Introduction of TRACE, and Cash Holdings

This table presents the results of cash holding regression using the Lehman bankruptcy filing and TRACE as exogenous shocks to bond liquidity. Columns 1 and 2 of Panel A show the results using the Lehman bankruptcy filing. The sample incorporates observations in 2007 and 2009. *Lehman* is an indicator that equals 1 for firm-year observations in year 2009, and 0 otherwise. Columns 3 and 4 of Panel A present the panel regression using the placebo period of the Lehman bankruptcy filing. The sample entails observations in 2010 and 2012. $Placebo_1$ is an indicator equal to 1 for firm-year observations in year 2010 and 0 otherwise. Columns 1 and 2 of Panel B display the results using the phase-in period of TRACE. The sample size ranges from 2002 to 2005. *Trace* takes the value of 1 for firms that report daily trading of bonds to TRACE and 0 otherwise. Columns 3 and 4 of Panel B show the empirical results of the placebo period of TRACE. The sample size ranges from 2006 to 2008. $Placebo_2$ is an indicator that takes the value of 1 for firms that report daily trading of bonds to TRACE and 0 otherwise. The definitions of other variables are provided in the Appendix. The models are estimated with year and firm fixed effects. The *t*-statistics reported in parentheses are based on heteroscedasticity-robust standard errors clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Lehman Bankruptcy Filing and Cash Holdings

	(1)	(2)	(3)	(4)
Lehman	0.012** (2.50)	0.072*** (12.17)		
$Placebo_1$			−0.014 (0.39)	0.001 (0.50)
$Coupon_{t-1}$	0.018*** (2.86)	−0.008 (0.78)	−0.039*** (16.07)	−0.009*** (3.14)
$Rate_{t-1}$	−0.510*** (18.59)	−0.002*** (4.76)	−0.528*** (24.37)	0.070*** (12.13)
MB_{t-1}	−0.493*** (9.37)	−0.216*** (6.91)	−0.701*** (12.45)	−0.242*** (10.67)
Cash $Flow_{t-1}/Assets_{t-1}$	−0.160*** (7.59)	−0.005 (0.05)	−0.323*** (20.77)	−0.051*** (12.83)
$Size_{t-1}$	0.021*** (3.25)	0.018*** (2.78)	−0.039*** (16.58)	−0.621*** (13.65)
$NWC_{t-1}/Assets_{t-1}$	−0.512*** (18.65)	−0.510*** (18.58)	−0.528*** (24.35)	−0.920*** (9.61)
$Capex_{t-1}$	−0.491*** (9.32)	−0.492*** (9.34)	−0.690*** (12.28)	−0.466*** (12.18)
Financial $leverage_{t-1}$	−0.165*** (7.81)	−0.161*** (7.60)	−0.326*** (21.08)	−0.111*** (11.56)
$Dividend_{t-1}$	−0.008 (0.74)	−0.008 (0.74)	−0.071*** (12.07)	0.003** (2.35)
$R\&D_{t-1}/Sales_{t-1}$	−0.002*** (4.78)	−0.002*** (4.79)	0.000 (0.12)	0.000 (0.11)
$Acquisition_{t-1}$	−0.213*** (6.80)	−0.215*** (6.89)	−0.326*** (7.37)	−0.330*** (7.45)
Industry $Sigma_{t-1}$	−0.008 (0.07)	−0.014 (0.13)	0.111 (0.64)	0.120 (0.69)
Intercept	0.433*** (17.59)	−0.008*** (2.81)	0.096* (1.90)	0.025*** (3.65)
Industry fixed effects	Yes	No	Yes	No
Firm fixed effects	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	962	962	1,032	1,031
Adj. R-squared	0.57	0.21	0.31	0.19

(*continues*)

TABLE 3. Lehman Bankruptcy Filing, Introduction of TRACE, and Cash Holdings *(continued)*

Panel B: The Introduction of Trace and Cash Holdings				
	(1)	(2)	(3)	(4)
TRACE	–0.003* (1.82)	–0.021*** (5.20)		
$Placebo_1$			–0.001 (1.21)	–0.003 (1.11)
$Coupon_{t-1}$	0.025*** (3.29)	–0.001 (0.13)	0.031*** (5.15)	–0.006 (1.19)
$Rate_{t-1}$	–0.005*** (3.26)	0.001 (0.71)	0.006 (0.56)	–0.015 (1.47)
MB_{t-1}	0.001 (0.35)	0.068*** (22.02)	0.001 (0.18)	0.066*** (20.55)
$Cash\ Flow_{t-1}/Assets_{t-1}$	–0.059 (0.99)	–1.225*** (19.51)	–0.062 (1.03)	–1.178*** (18.43)
$Size_{t-1}$	–0.035*** (3.60)	–0.053*** (14.60)	–0.039*** (3.95)	–0.057*** (14.22)
$NWC_{t-1}/Assets_{t-1}$	–0.334*** (7.52)	–0.598*** (19.48)	–0.327*** (7.34)	–0.725*** (20.09)
$Capex_{t-1}$	–0.432*** (5.10)	–0.881*** (10.77)	–0.427*** (5.04)	–0.937*** (10.11)
Financial $leverage_{t-1}$	–0.076** (2.21)	–0.474*** (19.09)	–0.071** (2.05)	–0.452*** (17.52)
$Dividend_{t-1}$	–0.011 (0.66)	–0.118*** (12.94)	–0.011 (0.63)	–0.109*** (11.17)
$R\&D_{t-1}/Sales_{t-1}$	0.001** (2.23)	0.003*** (3.35)	0.001** (2.21)	0.003*** (3.44)
$Acquisition_{t-1}$	–0.197*** (3.86)	–0.487*** (6.61)	–0.198*** (3.88)	–0.495*** (6.74)
Industry $Sigma_{t-1}$	0.760*** (4.56)	0.719*** (6.92)	0.720*** (4.26)	0.792*** (2.95)
Intercept	0.805*** (16.22)	0.484*** (6.41)	0.795*** (26.51)	0.519*** (6.80)
Industry fixed effects	Yes	No	Yes	No
Firm fixed effects	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	962	962	1,032	1,032
Adj. R-squared	0.48	0.31	0.50	0.31

In the above model, the dependent variable is excess returns, which are measured as stock *i*'s raw return in fiscal year *t* minus the return of a benchmark portfolio, which is the 25 size and book-to-market portfolios suggested by Fama and French (1993). The independent variable of interest is the two-way interaction between bond illiquidity and the change in cash holdings. This term captures the effect of bond illiquidity on the value of cash. M is the market value of equity, C is cash, E is earnings before extraordinary

(text continues on page 17)

TABLE 4. Bond Illiquidity and Value of Cash

This table reports the results of cash value regression using five continuous bond illiquidity measures from 2002 to 2012. The dependent variable, *excess returns,* is measured as the stock return of a firm in a given year minus the benchmark return from the Fama and French (1993) 25 size and book-to-market portfolios. Δ denotes a change in value from year *t*–1 to year *t*. *UD indicator* is a dummy variable that equals 1 for the years in which UD law is effective in a firm's state of incorporation, and 0 otherwise. Illiquidity measures *Amihud, IRC, Roll, Gibbs,* and *HL_Spread* are calculated using the models displayed in the text. The definitions of other variables are provided in the Appendix. The *t*-statistics based on heteroscedasticity-robust standard errors clustered by firm are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
$Amihud_{t-1}$	–0.002 (0.13)				
$Amihud_{t-1} \times (\Delta Cash_t/ME_{t-1})$	0.228*** (3.09)				
IRC_{t-1}		0.019 (1.58)			
$IRC_{t-1} \times (\Delta Cash_t/ME_{t-1})$		0.110* (1.67)			
$Roll_{t-1}$			0.038*** (3.12)		
$Roll_{t-1} \times (\Delta Cash_t/ME_{t-1})$			0.314*** (3.81)		
$Gibbs_{t-1}$				0.207 (0.86)	
$Gibbs_{t-1} \times (\Delta Cash_t/ME_{t-1})$				0.002* (1.80)	
HL_Spread_{t-1}					0.001* (1.91)
$HL\_Spread_{t-1} \times (\Delta Cash_t/ME_{t-1})$					0.009*** (31.15)
$Coupon_{t-1}$	0.005* (1.69)	0.005* (1.70)	0.005 (1.60)	–0.112*** (2.98)	–0.236*** (4.40)
$Rate_{t-1}$	0.026 (1.48)	0.028* (1.65)	0.017 (1.00)	–0.000 (0.28)	0.004** (2.50)
$\Delta Cash_t/ME_{t-1}$	0.776*** (4.41)	0.487*** (2.85)	0.793*** (5.51)	1.648*** (4.74)	1.494*** (3.53)
$\Delta Earnings_t/ME_{t-1}$	0.253*** (8.88)	0.088*** (6.51)	0.249*** (8.71)	0.426*** (5.23)	0.205** (2.19)
$\Delta Net\ Assets_t/ME_{t-1}$	0.043 (1.26)	0.022* (1.83)	0.032 (1.43)	0.024 (0.51)	–0.050 (0.84)
$\Delta R\&D_{t-1}/ME_{t-1}$	0.331* (1.68)	–0.628 (1.23)	–0.524 (1.01)	0.655 (0.69)	–0.305 (0.26)
$\Delta Interest_t/ME_{t-1}$	–0.519 (0.63)	0.267 (1.32)	–0.030 (0.06)	1.274 (1.38)	1.273 (1.18)
$\Delta Dividends_t/ME_{t-1}$	4.929** (2.10)	1.031 (1.49)	0.967 (1.41)	–3.462 (1.46)	–7.904*** (2.67)
$Cash_{t-1}/ME_{t-1}$	0.106*** (3.06)	0.041 (1.27)	–0.004 (0.24)	0.329*** (3.53)	1.079*** (5.93)
Financial $leverage_{t-1}$	–0.513 (1.01)	–0.677** (2.26)	–0.647** (2.14)	–1.613** (2.38)	–0.794 (0.99)
New $finance_t/ME_{t-1}$	–0.082* (1.79)	–0.221*** (3.66)	–0.116** (2.49)	–0.345*** (3.57)	–0.271** (2.26)
$Cash_{t-1}/ME_{t-1} \times \Delta Cash_{t-1}/ME_{t-1}$	–0.160 (0.92)	1.777*** (3.20)	0.079 (0.52)	–1.484** (2.15)	–0.285 (0.34)
Financial $leverage_t \times \Delta Cash_t/ME_{t-1}$	–0.513 (1.01)	–0.677** (2.26)	–0.647** (2.14)	–1.613** (2.38)	–0.794 (0.99)
Intercept	–0.006 (0.29)	–0.004 (0.18)	0.004 (0.20)	0.197*** (3.17)	0.128 (1.37)
Observations	3,896	3,896	3,896	3,896	3,896
Adj. R-squared	0.05	0.04	0.05	0.07	0.03

TABLE 5. Lehman Bankruptcy Filing, Introduction of TRACE, and Value of Cash

This table presents the results of the value of cash regression using the Lehman bankruptcy filing and TRACE as exogenous shocks to bond liquidity. Column 1 of Panel A shows the results using the Lehman bankruptcy filing. The sample incorporates observations in 2007 and 2009. *Lehman* is an indicator that equals 1 for firm-year observations in year 2009 and 0 otherwise. Column 2 of Panel A presents the panel regression using the placebo period of the Lehman bankruptcy filing. The sample entails observations in 2010 and 2012. $Placebo_1$ is an indicator that equals 1 for firm-year observations in year 2010 and 0 otherwise. Column 1 of Panel B displays the results using the phase-in period of TRACE. The sample size ranges from 2002 to 2005. *Trace* takes the value of 1 for firms that report daily trading of bonds to TRACE and 0 otherwise. Column 2 of Panel B shows the empirical results of the placebo period of TRACE using sample from 2006 to 2008. $Placebo_2$ is an indicator that takes the value of 1 for firms that report daily trading of bonds to TRACE and 0 otherwise. The definitions of other variables are provided in the Appendix. The models are estimated with year and firm fixed effects. The *t*-statistics reported in parentheses are based on heteroscedasticity-robust standard errors clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Lehman Bankruptcy Filing and the Value of Cash		
	(1)	(2)
Lehman	0.026 (0.09)	
Lehman × ($\Delta Cash_t/ME_{t-1}$)	0.321* (1.77)	
$Placebo_1$		0.412 (1.56)
$Placebo_1$ × ($\Delta Cash_t/ME_{t-1}$)		0.176 (1.00)
$Coupon_{t-1}$	0.020 (1.57)	–0.030*** (2.87)
$Rate_{t-1}$	–0.000* (1.92)	–0.000 (1.60)
$\Delta Cash_t/ME_{t-1}$	1.640*** (4.72)	1.508*** (3.56)
$\Delta Earnings_t/ME_{t-1}$	0.419*** (5.15)	0.198** (2.12)
$\Delta Net\ Assets_t/ME_{t-1}$	0.024 (0.51)	–0.055 (0.93)
$\Delta R\&D_t/ME_{t-1}$	0.610 (0.64)	–0.532 (0.46)
$\Delta Interest_t/ME_{t-1}$	1.304 (1.41)	1.167 (1.07)
$\Delta Dividends_t/ME_{t-1}$	–3.472 (1.46)	–8.248*** (2.78)
$Cash_{t-1}/ME_{t-1}$	0.327*** (3.54)	1.104*** (6.04)
Financial $leverage_t$	–0.302*** (5.45)	–0.180 (1.25)
New $finance_t/ME_{t-1}$	–0.346*** (3.58)	–0.272** (2.26)
$Cash_{t-1}/ME_{t-1} \times \Delta Cash_t/ME_{t-1}$	–1.443** (2.09)	–0.192 (0.23)
Financial $leverage_t \times \Delta Cash_t/ME_{t-1}$	–1.568** (2.31)	–0.668 (0.83)
Intercept	0.002 (0.18)	0.058*** (4.47)
Observations	951	1,121
Adj. R-squared	0.14	0.10

Panel B: Introduction of TRACE and the Value of Cash		
	(1)	(2)
TRACE	0.014*	
TRACE × ($\Delta Cash_t/ME_{t-1}$)	–0.222*	
$Placebo_2$		–0.001
$Placebo_2$ × ($\Delta Cash_t/ME_{t-1}$)		0.015
Other controls	Yes	Yes
Observations	1,164	1,321
Adj. R-squared	0.04	0.04

items, *NA* is assets minus cash, *RD* is research and development expenses, *I* is interest expenses, *D* is common dividends, *L* is market leverage, and *NF* is the sum of net new equity and debt issues. *Coupon* is the coupon rate of the bonds for specific firm. *Rate* is an indicator that equals to one for firms have the credit rating, and zero otherwise. The variable definitions are provided in the Appendix.

Table 4 reports the estimation results of the excess return model. First, the impact of bond illiquidity on the value of cash using five bond illiquidity measures. Liquidity measures *Amihud, IRC, Roll, Gibbs,* and *HL_Spread* are estimated. The estimation results show that the coefficients on the two-way interaction *Amihud* × *ΔCash, IRC* × *ΔCash, Roll* × *ΔCash, Gibbs* × *ΔCash,* and *HL_Spread* × *ΔCash* are positive (0.228, 0.110, 0.314, 0.002, and 0.009, respectively) and statistically significant. Overall, the results in this session suggest a positive relation between bond illiquidity and cash holdings.

To mitigate the concern that both bond illiquidity and firm value can be jointly correlated with unobservable firm characteristics, two exogenous shocks are used to bond illiquidity to identify the causal relation between bond illiquidity and the value of cash. Specifically, *Amihud, IRC, Roll, Gibbs,* and *HL_Spread* are replaced with Lehman and TRACE indicator variables. To capture the effect of each shock, this study focuses on the year preceding and the year after the shock. If deteriorated bond liquidity motivates firms to increase cash reserves to avoid future higher cost of external financing, the coefficient of the interaction term *Lehman* × *ΔCash* (*TRACE* × *ΔCash*) is expected to be positive (negative). The results shown in Table 5 are consistent with the expectation: The coefficient of *Lehman* × *ΔCash* in column 1, Panel A of Table 5 is significantly positive (0.321), whereas the coefficient of *TRACE* × *ΔCash* in column 1 of Panel B is significantly negative (–0.822). The economic impact is also substantial: Holding other variables unchanged at their sample means, a decline in bond liquidity associated with the Lehman bankruptcy filing decreases the value of cash by $0.142. In addition, the results in columns 2 of Panels A and B show little placebo effect on cash values. This evidence suggests that the finding of a positive relation between cash holding, and bond illiquidity is not likely driven by other confounding effects. In summary, the results in

Table 5 lend further support to the argument that bond illiquidity enhances the value of cash.

If bond illiquidity increases transaction cost and thus makes it difficult for firms to obtain external financing, the value implication of incremental cash holdings should be more pronounced for financially constrained firms. This paper further examines this possibility next.

We adopt five measures of financial constraints that include MB ratio, payout ratio, WW index (Whited and Wu 2006), credit rating status (Faulkender and Petersen 2006), and SA index (Hadlock and Pierce 2010) in the main context. Following Lamont, Polk, and Saaá-Requejo (2001) that a firm with a high market-to-book ratio is more likely to be financially constrained, this paper uses this measure as the first proxy for financial constraint. The payout ratio is measured as the value of dividends and common stock repurchases divided by operating income. The WW index is calculated as:

$$\text{WW index} = -0.091 \times CF - 0.062 \times DIVPOS + 0.021 \times TLTD - 0.044 \times LNTA + 0.102 \times ISG - 0.035 \times SG$$

Where

CF is the ratio of cash flow to the book value of assets

DIVPOS is a dummy variable that equals 1 if the firm pays cash dividends in a given year, and 0 otherwise

TLTD is the ratio of the long-term debt to the book value of assets

LNTA is the natural log transformation of the book value of assets

ISG is the firm's three-digit SIC industry sales growth

SG is the firm's sales growth

The SA index is calculated as:

$$\text{SA index} = -0.737 \times \text{Assets} + 0.043 \times \text{Assets}^2 - 0.040 \times \text{Age}$$

Where

Assets is the log of the minimum value between actual book value of assets and \$4.5 billion

Age is the minimum value between firms' age and 37 years

We construct the market-to-book ratio indicator, labeled MB, which takes the value of 1 for market-to-book ratio above the sample median and 0 otherwise. By construction, financially constrained (unconstrained) firms are those with (without) credit rating status, larger (smaller) MB ratio, high (low) WW index values, high (low) SA index values, and positive (zero) payout ratio. Except for the payout ratio, we use the sample medians of the respective financial constraint measures to sort sample firms into financially constrained and unconstrained subgroups.

(text continues on page 25)

TABLE 6. Value of Cash and Financial Constraints

This table presents the value implication of cash holdings regressions for financially constrained (FC) and unconstrained (Non-FC) subgroups. The levels of financial constraints are determined based on MB ratio, payout ratio, WW index, or SA index. In Panel A, *MB_dummy* is an indicator that equals 1 if the value of the market-to-book ratio of a firm-year observation is above its sample median and 0 otherwise. In Panel B, *D _dummy* is an indicator that equals 1 if the value of the dividend ratio of a firm-year observation is larger than zero, and 0 otherwise. In Panel C, *WW _dummy* is an indicator that equals 1 if the value of the WW index of a firm-year observation is above its sample median and 0 otherwise. The WW index is calculated as: WW index = −0.091 × *CF* − 0.062 × *DIVPOS* + 0.021 × *TLTD* − 0.044 × *LNTA* + 0.102 × *ISG* −0.035 × *SG*, where *CF* is the ratio of cash flow to the book value of assets; *DIVPOS* is a dummy variable that equals to one if the firm pays cash dividends in a given year, and zero otherwise; *TLTD* is the ratio of the long-term debt to the book value of assets; *LNTA* is the natural log transformation of the book value of assets; *ISG* is the firm's three-digit SIC industry sales growth; and *SG* is the firm's sales growth. In Panel D, *SA _dummy* is an indicator that equals 1 if the value of the Size-age index of a firm-year observation is above its sample median and 0 otherwise. The SA index is calculated as: SA index = −0.737 × Assets + 0.043 × $Assets^2$ − 0.040 × Age, where *Assets* is the log of the minimum value between actual book value of assets and \$4.5 billion, and *Age* is the minimum value between firms' age and thirty-seven years. Panel E, *C_dummy* is an indicator that equals 1 if the firms have credit rating status. Panel F reports the results for the Lehman Bankruptcy Filing. Panel G reports the results for the introduction of TRACE. The definitions of other variables are provided in the Appendix. The *t*-statistics based on heteroscedasticity-robust standard errors clustered by firm are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: MB_dummy					
	(1)	(2)	(3)	(4)	(5)
$Amihud_{t-1}$	−0.021 (1.38)				
$Amihud_{t-1}$ × ($\Delta Cash_t/ME_{t-1}$)	−0.440*** (2.66)				
$Amihud_{t-1}$ × MB_dummy_{t-1} × $\Delta Cash_t/ME_{t-1}$	0.391** (2.14)				
IRC_{t-1}		0.001 (0.06)			
IRC_{t-1} × $\Delta Cash_t/ME_{t-1}$		−0.358*** (3.15)			
IRC_{t-1} × MB_dummy_{t-1} × $\Delta Cash_t/ME_{t-1}$		0.648*** (3.06)			
$Roll_{t-1}$			0.031** (2.05)		
$Roll_{t-1}$ × $\Delta Cash_t/ME_{t-1}$			−0.835*** (4.15)		
$Roll_{t-1}$ × MB_dummy_{t-1} × $\Delta Cash_t/ME_{t-1}$			0.744*** (3.44)		
$Gibbs_{t-1}$				0.110* (1.70)	
$Gibbs_{t-1}$ × $\Delta Cash_t/ME_{t-1}$				0.030 (1.07)	
$Gibbs_{t-1}$ × MB_dummy_{t-1} × $\Delta Cash_t/ME_{t-1}$				0.082*** (1.84)	
HL_Spread_{t-1}					−0.055 (1.42)
HL_Spread_{t-1} × $\Delta Cash_t/ME_{t-1}$					0.001 (0.44)
HL_Spread_{t-1} × MB_dummy_{t-1} × $\Delta Cash_t/ME_{t-1}$					0.225*** (3.14)
MB_dummy_{t-1}	0.053*** (3.21)	0.052*** (3.15)	0.051*** (3.08)	0.057*** (7.39)	0.024 (1.09)
$Coupon_{t-1}$	0.006* (1.67)	0.006* (1.65)	0.007* (1.73)	0.544*** (5.17)	0.037 (0.13)
$Rate_{t-1}$	0.023 (1.11)	0.020 (0.94)	0.015 (0.69)	−0.017 (1.57)	0.097 (1.10)
$\Delta Cash_t/ME_{t-1}$	1.052*** (9.50)	0.960*** (9.14)	1.048*** (9.85)	0.015*** (10.61)	0.003 (1.16)
$\Delta Earnings_t/ME_{t-1}$	0.151*** (8.46)	0.156*** (8.72)	0.155*** (8.66)	−0.117*** (6.31)	0.059 (1.50)

(*continues*)

TABLE 6. **Value of Cash and Financial Constraints** *(continued)*

	(1)	(2)	(3)	(4)	(5)
ΔNet Assets$_t$/ME$_{t-1}$	−0.022 (1.12)	−0.021 (1.07)	−0.022 (1.11)	−0.008*** (4.13)	0.002 (0.17)
ΔR&D$_{t-1}$/ME$_{t-1}$	−0.086 (0.35)	−0.156 (0.63)	−0.104 (0.41)	−0.380*** (20.76)	−0.215*** (3.61)
ΔInterest$_t$/ME$_{t-1}$	−0.552* (1.66)	−0.463 (1.40)	−0.608* (1.83)	−0.532*** (9.91)	−0.354*** (4.41)
ΔDividends$_t$/ME$_{t-1}$	−0.215 (0.69)	−0.285 (0.91)	−0.196 (0.63)	−0.329*** (23.65)	−0.056 (1.45)
Cash$_{t-1}$/ME$_{t-1}$	0.163*** (3.98)	0.146*** (3.56)	0.141*** (3.48)	−0.056*** (8.62)	0.000 (0.33)
Financial leverage$_t$	−0.179*** (3.91)	−0.183*** (3.99)	−0.174*** (3.81)	0.049*** (14.14)	0.036 (1.24)
New finance$_t$/ME$_{t-1}$	0.039 (1.31)	0.052* (1.77)	0.032 (1.08)	−0.266*** (6.64)	−0.198*** (3.48)
Cash$_{t-1}$/ME$_{t-1}$ × ΔCash$_{t-1}$/ME$_{t-1}$	−0.136*** (5.34)	−0.117*** (4.56)	−0.147*** (5.71)	1.373*** (4.57)	0.173 (0.87)
Financial leverage$_t$ × ΔCash$_t$/ME$_{t-1}$	−1.148*** (5.80)	−0.979*** (5.20)	−1.047*** (5.57)	−0.029*** (2.84)	−0.004 (0.44)
Intercept	0.001 (0.03)	−0.000 (0.02)	−0.007 (0.29)	−0.067* (1.81)	0.023 (0.59)
Observations	4,192	4,192	4,192	4,192	4,192
Adj. R-squared	0.06	0.03	0.09	0.08	0.02
Panel B: D_dummy					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Amihud$_{t-1}$	0.061*** (3.05)				
Amihud$_{t-1}$ × (ΔCash$_t$/ME$_{t-1}$)	0.544*** (5.19)				
Amihud$_{t-1}$ × D_dummy$_{t-1}$ × ΔCash$_t$/ME$_{t-1}$	0.412*** (5.87)				
IRC$_{t-1}$		0.026 (0.63)			
IRC$_{t-1}$ × ΔCash$_t$/ME$_{t-1}$		−0.005 (0.01)			
IRC$_{t-1}$ × D_dummy$_{t-1}$ × ΔCash$_t$/ME$_{t-1}$		0.553* (1.94)			
Roll$_{t-1}$			−0.184 (1.54)		
Roll$_{t-1}$ × ΔCash$_t$/ME$_{t-1}$			0.193** (2.41)		
Roll$_{t-1}$ × D_dummy$_{t-1}$ × ΔCash$_t$/ME$_{t-1}$			0.295*** (6.22)		
Gibbs$_{t-1}$				0.329*** (3.95)	
Gibbs$_{t-1}$ × ΔCash$_t$/ME$_{t-1}$				0.373** (2.30)	
Gibbs$_{t-1}$ × D_dummy$_{t-1}$ × ΔCash$_t$/ME$_{t-1}$				0.924*** (3.28)	
HL_Spread$_{t-1}$					0.164*** (5.75)
HL_Spread$_{t-1}$ × ΔCash$_t$/ME$_{t-1}$					0.533*** (4.25)
HL_Spread$_{t-1}$ × D_dummy$_{t-1}$ × ΔCash$_t$/ME$_{t-1}$					0.232*** (2.88)

Panel B: D_dummy (continued)					
	(1)	(2)	(3)	(4)	(5)
D_dummy_{t-1}	−0.688 (0.95)	0.373** (2.30)	−0.623 (0.85)	−0.060 (0.88)	0.206*** (4.10)
$\Delta Cash_t/ME_{t-1}$	1.544*** (5.19)	1.605*** (4.35)	1.440** (2.07)	1.924*** (3.28)	1.564** (2.26)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	3,991	3,991	3,991	3,991	3,991
Adj. R-squared	0.05	0.06	0.06	0.02	0.09
Panel C: WW_dummy					
	(1)	(2)	(3)	(4)	(5)
$Amihud_{t-1}$	−0.060 (1.18)				
$Amihud_{t-1} \times (\Delta Cash_t/ME_{t-1})$	−0.826 (0.82)				
$Amihud_{t-1} \times WW\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$	0.789* (1.90)				
IRC_{t-1}		0.944*** (5.98)			
$IRC_{t-1} \times \Delta Cash_t/ME_{t-1}$		−0.193 (1.55)			
$IRC_{t-1} \times WW\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$		0.266** (2.57)			
$Roll_{t-1}$			0.732* (1.84)		
$Roll_{t-1} \times \Delta Cash_t/ME_{t-1}$			1.110*** (2.75)		
$Roll_{t-1} \times WW\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$			0.986*** (6.23)		
$Gibbs_{t-1}$				0.553* (1.94)	
$Gibbs_{t-1} \times \Delta Cash_t/ME_{t-1}$				−0.184 (1.54)	
$Gibbs_{t-1} \times WW\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$				0.193** (2.41)	
HL_Spread_{t-1}					0.233*** (2.89)
$HL\_Spread_{t-1} \times \Delta Cash_t/ME_{t-1}$					−0.071 (1.38)
$HL\_Spread_{t-1} \times WW\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$					0.098* (1.79)
WW_dummy_{t-1}	−0.295*** (6.22)	−0.119 (0.96)	0.295*** (6.22)	0.220* (1.78)	0.295*** (6.22)
$\Delta Cash_t/ME_{t-1}$	0.329*** (3.95)	0.250** (2.40)	0.329*** (3.95)	−0.257** (2.48)	0.329*** (3.95)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	3,991	3,991	3,991	3,991	3,991
Adj. R-squared	0.08	0.04	0.07	0.06	0.04

(*continues*)

TABLE 6. Value of Cash and Financial Constraints *(continued)*

Panel D: SA_dummy					
	(1)	(2)	(3)	(4)	(5)
$Amihud_{t-1}$	0.026 (0.63)				
$Amihud_{t-1} \times (\Delta Cash_t/ME_{t-1})$	−0.005 (0.01)				
$Amihud_{t-1} \times SA\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$	0.553* (1.94)				
IRC_{t-1}		0.412*** (5.87)			
$IRC_{t-1} \times \Delta Cash_t/ME_{t-1}$		0.026 (0.63)			
$IRC_{t-1} \times SA\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$		1.061*** (3.05)			
$Roll_{t-1}$			−0.057 (1.11)		
$Roll_{t-1} \times \Delta Cash_t/ME_{t-1}$			−1.010 (1.01)		
$Roll_{t-1} \times SA\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$			1.783* (1.90)		
$Gibbs_{t-1}$				0.089** (2.08)	
$Gibbs_{t-1} \times \Delta Cash_t/ME_{t-1}$				−0.669 (1.12)	
$Gibbs_{t-1} \times SA\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$				1.099** (2.32)	
HL_Spread_{t-1}					0.100** (2.40)
$HL\_Spread_{t-1} \times \Delta Cash_t/ME_{t-1}$					−0.052 (0.84)
$HL\_Spread_{t-1} \times SA\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$					0.983* (1.93)
SA_dummy_{t-1}	−0.073 (0.69)	−0.075 (0.71)	−0.048 (0.45)	−0.057 (0.68)	−0.073 (0.69)
$\Delta Cash_t/ME_{t-1}$	1.193** (2.35)	1.195** (2.39)	2.165** (2.04)	1.031 (0.74)	1.033 (0.81)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	3,991	3,991	3,991	3,991	3,991
Adj. R-squared	0.08	0.04	0.07	0.06	0.04
Panel E: C_dummy					
	(1)	(2)	(3)	(4)	(5)
$Amihud_{t-1}$	−0.036*** (6.65)				
$Amihud_{t-1} \times (\Delta Cash_t/ME_{t-1})$	0.105*** (4.09)				
$Amihud_{t-1} \times C\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$	0.031* (1.96)				
IRC_{t-1}		−0.055*** (9.82)			
$IRC_{t-1} \times \Delta Cash_t/ME_{t-1}$		−0.016 (1.32)			

Panel E: C_dummy (continued)					
	(1)	(2)	(3)	(4)	(5)
$IRC_{t-1} \times C\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$		0.357* (1.92)			
$Roll_{t-1}$			−0.019*** (16.79)		
$Roll_{t-1} \times \Delta Cash_t/ME_{t-1}$			−0.126*** (26.15)		
$Roll_{t-1} \times C\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$			0.011* (1.76)		
$Gibbs_{t-1}$				−0.070** (1.97)	
$Gibbs_{t-1} \times \Delta Cash_t/ME_{t-1}$				−0.093*** (16.22)	
$Gibbs_{t-1} \times C\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$				0.426*** (17.45)	
HL_Spread_{t-1}					−0.684*** (18.48)
$HL\_Spread_{t-1} \times \Delta Cash_t/ME_{t-1}$					−0.057*** (22.68)
$HL\_Spread_{t-1} \times C\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$					−0.727*** (36.03)
C_dummy_{t-1}	−0.495*** (33.92)	−0.325*** (24.35)	−1.840*** (25.78)	−1.073*** (15.83)	−0.525*** (21.84)
$\Delta Cash_t/ME_{t-1}$	0.296*** (58.08)	0.350*** (42.76)	0.765*** (30.70)	1.179*** (28.43)	0.593*** (40.34)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	3,991	3,991	3,991	3,991	3,991
Adj. R-squared	0.12	0.14	0.21	0.22	0.32
Panel F: Lehman Bankruptcy Filing					
	(1)	(2)	(3)	(4)	(5)
MB_dummy_{t-1}	0.055*** (12.63)				
$Lehman \times MB\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$	1.087*** (14.60)				
KZ_dummy_{t-1}		0.619 (0.53)			
$Lehman \times KZ\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$		1.372* (1.75)			
WW_dummy_{t-1}			0.096 (0.24)		
$Lehman \times WW\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$			1.532* (1.80)		
SA_dummy_{t-1}				0.619*** (15.57)	
$Lehman \times SA\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$				2.372*** (28.54)	
C_dummy_{t-1}					0.039 (0.84)
$Lehman \times C\_dummy_{t-1} \times \Delta Cash_t/ME_{t-1}$					−0.016 (1.29)

(continues)

TABLE 6. Value of Cash and Financial Constraints *(continued)*

	(1)	(2)	(3)	(4)	(5)
Lehman	0.305*** (5.46)	0.087*** (14.62)	0.672*** (12.95)	0.210*** (15.16)	0.087*** (50.19)
$\Delta Cash_t/ME_{t-1}$	1.074*** (10.00)	1.055*** (12.69)	1.894*** (5.19)	2.074*** (10.07)	0.252*** (7.65)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	920	920	920	920	920
Adj. R-squared	0.15	0.34	0.08	0.12	0.11
Panel G: Introduction of TRACE					
	(1)	(2)	(3)	(4)	(5)
MB_dummy_{t-1}	−0.366*** (14.95)				
Trace × MB_dummy_{t-1} × $\Delta Cash_t/ME_{t-1}$	−2.438* (1.73)				
KZ_dummy_{t-1}		−0.626 (0.63)			
Trace × KZ_dummy_{t-1} × $\Delta Cash_t/ME_{t-1}$		−1.098*** (15.29)			
WW_dummy_{t-1}			−0.382* (1.83)		
Trace × WW_dummy_{t-1} × $\Delta Cash_t/ME_{t-1}$			−1.554* (1.76)		
SA_dummy_{t-1}			−0.210*** (15.15)		
Trace × SA_dummy_{t-1} × $\Delta Cash_t/ME_{t-1}$			−0.846* (1.73)		
Trace	0.044 (1.33)	0.044 (1.31)	1.007** (2.46)	0.788* (1.76)	
Trace × $\Delta Cash_t/ME_{t-1}$	−1.314*** (4.23)	−1.301*** (8.21)	−0.541*** (5.32)	−1.121 (0.01)	
C_dummy_{t-1}					0.254*** (25.05)
Lehman × C_dummy_{t-1} × $\Delta Cash_t/ME_{t-1}$					−0.883* (1.85)
$\Delta Cash_t/ME_{t-1}$	−0.739*** (7.56)	−0.874*** (5.12)	−0.087* (1.70)	−0.051*** (10.00)	0.057*** (6.62)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1,032	1,032	1,032	1,032	1,032
Adj. R-squared	0.05	0.06	0.06	0.02	0.06

In Panel A of Table 6, the three-way interaction term *Liquidity* × *MB* × *ΔCash* is the variable of interest. The empirical results reported in Panel A, Table 6 indicate a positive and significant relation for the three-way interaction variable, suggesting that the value of cash is higher for firms with both higher growth opportunities and lower bond liquidity. The results are robust across panels using different proxies of bond illiquidity and financial constraints. Collectively, the results show that bond illiquidity increases cash holdings and the value of cash.

ROBUSTNESS CHECK

We run a battery of robustness checks and, for brevity, report some of the results (but the remaining results are available from the authors). To mitigate the concerns that bond illiquidity measures only capture the impact of cost of debt, we control for another proxy of bond illiquidity, *Yield Slope,* defined as the difference between 10-year and 2-year Treasury rates. The results reported in Table 7 indicate the relations between bond illiquidity and cash holdings, and value of cash remain unchanged.

Second, prior studies found that stock liquidity has an impact on corporate financial policies. To alleviate the concerns that the results are driven by stock liquidity, we additionally control for stock liquidity measure *Amihud* in the cash holdings and value of cash regressions. The results in Table 8 show the positive relation between bond illiquidity and cash holdings, and value of cash are insensitive to the inclusion of stock liquidity. Third, to alleviate the concerns that cash holdings increase with the decline in dividends, we additionally check the impact of bond illiquidity on corporate dividend policy. Untabulated results do not show any significant relation between bond illiquidity and dividend policies.

Last, we explore how debt maturity affects the relation between bond illiquidity and corporate cash holdings. Longer debt maturity may lead to a decline in bond liquidity, which in turn has a negative impact on the level of cash reserves. To test this possibility, we control corporate debt due in one year, two years, and three years. In particular, we construct the variables to control for the debt maturity:

1. ST1 is the ratio of debt in current liabilities to total debt
2. ST2 is the ratio of debt in current liabilities plus debt maturing in two years to total debt
3. ST3 is the ratio of debt in current liabilities plus debt maturing in two or three years to total debt (the sum of debt in current liabilities plus long-term debt)

The results reported in Table 9 show that while bond illiquidity still has a significant and positive impact on cash reserves, the coefficients of the measures of bond illiquidity do not decrease with the debt maturity. The above evidence shows that the impact of bond illiquidity on corporate cash holdings is beyond the impact of debt maturity on a firm's cash reserve.

(text continues on page 31)

TABLE 7. Bond Illiquidity, Cash Holdings, and Value of Cash: Controlling for Cost of Debt

This table reports the results controlling for Yield Slope. Panel A reports the results of cash holdings regressions and Panel B reports the value of cash regressions using liquidity measures *Amihud, IRC, Roll, Gibbs,* and *HL_Spread.* Panel C presents the results of cash holding regression using the Lehman bankruptcy filing and Panel D presents the results of TRACE as exogenous shocks to bond liquidity. The definitions of other variables are provided in the Appendix. The *t*-statistics based on heteroscedasticity-robust standard errors clustered by firm are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Cash Holdings Regressions					
	(1)	(2)	(3)	(4)	(5)
$Amihud_{t-1}$	0.015*** (9.08)				
IRC_{t-1}		0.063*** (7.45)			
$Roll_{t-1}$			0.355** (2.42)		
$Gibbs_{t-1}$				0.628* (1.71)	
HL_Spread_{t-1}					0.354* (1.76)
Yield $Slope_{t-1}$	0.358*** (24.71)	0.043*** (13.00)	0.550*** (19.68)	0.359*** (25.62)	0.055*** (13.57)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,870	3,870	3,870	3,870	3,870
Adj. R-squared	0.10	0.19	0.34	0.24	0.17

Panel B: Value of Cash Regressions					
	(1)	(2)	(3)	(4)	(5)
$Amihud_{t-1}$	0.293 (0.47)				
$Amihud_{t-1} \times (\Delta Cash_t/ME_{t-1})$	0.903*** (4.46)				
IRC_{t-1}		0.672*** (5.95)			
$IRC_{t-1} \times (\Delta Cash_t/ME_{t-1})$		1.137*** (10.76)			
$Roll_{t-1}$			0.511 (0.20)		
$Roll_{t-1} \times (\Delta Cash_t/ME_{t-1})$			1.382*** (3.83)		
$Gibbs_{t-1}$				0.292*** (10.45)	
$Gibbs_{t-1} \times (\Delta Cash_t/ME_{t-1})$				0.903* (1.72)	
HL_Spread_{t-1}					0.846 (1.53)
$HL\_Spread_{t-1} \times (\Delta Cash_t/ME_{t-1})$					0.593*** (5.12)
Yield $Slope_{t-1}$	–0.009 (1.52)	–0.046 (1.27)	–0.018 (1.50)	–0.010 (1.55)	–0.048 (1.31)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	3,690	3,690	3,690	3,690	3,690
Adj. R-squared	0.32	0.28	0.32	0.22	0.25

Panel C: Lehman Bankruptcy Filing, Introduction of Trace, and Cash Holdings				
	(1)	(2)	(3)	(4)
Lehman	0.088* (1.83)	−0.086* (1.95)		
Trace			−0.113* (1.79)	−0.119* (1.66)
Yield Slope$_{t-1}$	0.067 (0.49)	0.065 (0.47)	0.057 (0.43)	0.054 (0.41)
Controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	No	Yes	No
Firm fixed effects	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	932	932	1,012	1,012
Adj. R-squared	0.32	0.24	0.30	0.28
Panel D: Lehman Bankruptcy Filing, Introduction of Trace, and Value of Cash				
	(1)	(2)	(3)	(4)
Lehman	0.093** (2.53)	−0.085** (2.42)		
Lehman × $\Delta Cash_t/ME_{t-1}$	1.892* (1.75)	1.126* (1.71)		
Trace			−0.723 (1.12)	−0.778 (0.94)
Trace × $\Delta Cash_t/ME_{t-1}$			−1.702*** (2.70)	−1.332* (1.79)
$\Delta Cash_t/ME_{t-1}$			−1.702*** (2.70)	−1.332* (1.79)
	−0.968 (0.52)	−0.971 (0.54)	0.949** (2.38)	0.953*** (3.67)
Yield Slope$_{t-1}$	−0.024 (0.53)	−0.026 (0.59)	−0.006 (0.13)	−0.013 (0.40)
Controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	No	Yes	No
Firm fixed effects	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	951	951	1,027	1,027
Adj. R-squared	0.37	0.42	0.27	0.20

TABLE 8. Bond Illiquidity, Cash Holdings, and Value of Cash: Controlling for Stock Liquidity

This table reports the results of the cash holdings and value of cash regressions controlling for stock liquidity measure *Amihud*. Panel A reports the results of cash holdings regressions and Panel B reports the value of cash regressions using liquidity measures *Amihud, IRC, Roll, Gibbs,* and *HL_Spread.* Panel C presents the results of cash holding regression using the Lehman bankruptcy filing and Panel D presents the results of TRACE as exogenous shocks to bond liquidity. The definitions of other variables are provided in the Appendix. The *t*-statistics based on heteroscedasticity-robust standard errors clustered by firm are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Cash Holdings Regressions

	(1)	(2)	(3)	(4)	(5)
$Amihud_{t-1}$	0.021* (1.90)				
IRC_{t-1}		0.046*** (3.00)			
$Roll_{t-1}$			0.011** (2.55)		
$Gibbs_{t-1}$				0.007*** (3.01)	
HL_Spread_{t-1}					0.020* (1.89)
Stock $Liquidity_{t-1}$	0.007*** (3.01)	0.079 (1.01)	0.025 (0.89)	0.040 (1.17)	0.105 (0.72)
Controls	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	3,798	3,798	3,798	3,798	3,798
Adj. R-squared	0.21	0.53	0.37	0.15	0.11

Panel B: Value of Cash Regressions

	(1)	(2)	(3)	(4)	(5)
$Amihud_{t-1}$	0.056 (0.92)				
$Amihud_{t-1} \times (\Delta Cash_t/ME_{t-1})$	0.927*** (8.80)				
IRC_{t-1}		0.040 (1.17)			
$IRC_{t-1} \times (\Delta Cash_t/ME_{t-1})$		–0.015*** (8.97)			
$Roll_{t-1}$			0.105 (0.72)		
$Roll_{t-1} \times (\Delta Cash_t/ME_{t-1})$			–0.062*** (7.27)		
$Gibbs_{t-1}$				0.056 (0.92)	
$Gibbs_{t-1} \times (\Delta Cash_t/ME_{t-1})$				–0.027*** (8.65)	
HL_Spread_{t-1}					–0.018 (1.54)
$HL\_Spread_{t-1} \times (\Delta Cash_t/ME_{t-1})$					0.011** (2.55)
Stock $Liquidity_{t-1}$	–0.009 (1.52)	–0.046 (1.27)	–0.018 (1.50)	–0.010 (1.55)	–0.048 (1.31)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	3,632	3,632	3,632	3,632	3,632
Adj. R-squared	0.24	0.43	0.33	0.43	0.39

Panel C: Lehman Bankruptcy Filing, Introduction of Trace, and Cash Holdings				
	(1)	(2)	(3)	(4)
Lehman	0.237*** (6.32)	0.242*** (6.55)		
Trace			−0.164*** (2.59)	−0.157** (2.49)
Stock Liquidity$_{t-1}$	0.221 (0.54)	0.219 (0.53)	0.119 (0.30)	0.173*** (9.88)
Controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	No	Yes	No
Firm fixed effects	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	954	954	954	954
Adj. R-squared	0.37	0.26	0.31	0.33
Panel D: Lehman Bankruptcy Filing, Introduction of Trace, and Value of Cash				
	(1)	(2)	(3)	(4)
Lehman	0.016 (0.48)	0.009 (0.27)		
Lehman × $\Delta Cash_t/ME_{t-1}$	1.260*** (6.89)	1.248*** (6.18)		
Trace			0.033 (1.03)	0.034 (0.88)
Trace × $\Delta Cash_t/ME_{t-1}$			−1.083** (2.31)	−1.082** (2.34)
$\Delta Cash_t/ME_{t-1}$	−0.657 (1.00)	−0.675 (1.03)	1.098 (1.08)	1.093 (0.97)
Stock Liquidity$_{t-1}$	0.823 (1.30)	1.006 (1.60)	−0.019 (0.46)	−0.024 (0.72)
Controls	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	No	Yes	No
Firm fixed effects	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	1,009	1,009	1,009	1,009
Adj. R-squared	0.32	0.24	0.24	0.2

TABLE 9. Bond Illiquidity, Cash Holdings, and Value of Cash: Controlling for Debt Maturity

This table reports the results of the cash holdings and value of cash regressions controlling for debt maturity measure. Panel A presents the results of cash holding regression using the Lehman bankruptcy filing and Panel B presents the results of TRACE as exogenous shocks to bond liquidity. ST1 is the ratio of debt in current liabilities (*dlc*) to total debt (*dlc* + *dltt*). ST2 is the ratio of debt in current liabilities (*dlc*) plus debt maturing in two years (*dd2*) to total debt (*dlc* + *dltt*). ST3 is the ratio of debt in current liabilities (*dlc*) plus debt maturing in two or three years (*dd2* + *dd3*) to total debt (the sum of debt in current liabilities plus long-term debt, i.e., *dlc* + *dltt*). The definitions of other variables are provided in the Appendix. The *t*-statistics based on heteroscedasticity-robust standard errors clustered by firm are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Lehman Bankruptcy Filing and Cash Holdings			
	(1)	(2)	(3)
Lehman	0.044* (1.48)	0.112* (1.70)	0.137* (1.82)
ST1	–0.036*** (6.65)		
ST2		0.005 (0.36)	
ST3			–0.041 (1.55)
Controls	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	1,009	1,009	1,009
Adj. R-squared	0.58	0.82	0.51
Panel B: Introduction of Trace and Cash Holdings			
	(1)	(2)	(3)
Trace	–0.061** (2.34)	–0.011* (1.77)	–0.019* (1.81)
ST1	–0.014** (2.03)		
ST2		–0.045 (0.70)	
ST3			0.154 (1.23)
Controls	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	952	952	952
Adj. R-squared	0.28	0.32	0.13

CONCLUSION

This paper examines the impact of bond illiquidity on firms' cash holdings and the value of cash. Exploiting two exogenous bond liquidity shocks, namely, the inception of TRACE and the Lehman bankruptcy filing, as well as the traditional measures of bond illiquidity. This paper finds that bond illiquidity increases corporate cash holdings. Further tests show that bond illiquidity increases the value of cash, and such effect is more pronounced for financially constrained firms, suggesting that bond illiquidity induces firms to maintain larger cash reserves to reduce underinvestment.

This paper contributes to literature in several ways. First, our paper adds to the well-developed literature of the determinants of corporate cash holdings by showing that bond illiquidity is another important determinant of cash holdings. Second, our paper complements prior studies that investigate the impact of credit rights or bond liquidity on corporate financial policies. To the best of our knowledge, this paper is the first one to exploit exogenous bond liquidity shocks, as well as the traditional measures of bond illiquidity, to establish the causal relation between bond liquidity and corporate cash holdings. This study adds value to policy making and corporate decisioning process as we suggest that bond illiquidity can be altered by the enactment of laws, and corporate cash holdings are important for corporate liquidity. Lastly, our paper contributes to the stream of literature that focuses on the impact of liquidity on corporate governance and firm policies. We provide first-time evidence about the causal relation between bond illiquidity and cash holdings and the value of cash.

We believe this research can be beneficial for regulators when they formulate policies relating to bond liquidity and for practitioners when they make decisions on corporate liquidity and investments.

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Appendix

Definition of Variables

Variable	Definition
Acquisition	Acquisitions over a firm’s total assets in fiscal year *t*
Cash/Assets	The ratio of cash plus marketable securities to total assets
Rate	An indicator that equals 1 for firms with the credit ratings, and 0 otherwise
Coupon	The coupon rate of the bonds for a firm
Cash flow/Assets	Operating income before depreciation, minus interest, taxes, and common dividends, divided by a firm’s total assets
Capex	Capital expenditures over a firm’s total assets
Decimal	An indicator that takes the value of 1 for the fiscal year after decimalization and 0 for the fiscal year preceding decimalization
Dividend	An indicator that equals 1 for the fiscal year that firms pay a dividend and 0 otherwise
Financial leverage	Long-term debt plus debt in current liabilities, all divided by a firm’s total assets
Industry Sigma	The 2-digit SIC industry average standard deviation of cash flow over assets in the prior 10 years (with at least 3 observations)
M/B	Measured as book value of total assets minus book value of common equity plus the market value of equity, all divided by book value of total assets
NF	The sum of net new equity and debt issues, which is calculated as the sale of common and preferred stock minus the purchase of common and preferred stock plus issuance of long-term debt minus reduction of long-term debt
NWC	Net working capital, measured as working capital minus cash and marketable securities, divided by a firm’s total assets
R&D/Sales	Ratio of R&D expenditures to sales, set to 0 if missing
Size	Natural logarithm of book assets adjusted to 2012 dollar value using the consumer price index (CPI) reported on the website of the Federal Reserve Bank of St. Louis (https://www.stlouisfed.org/)

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Benchmarking the Financial Performance of Office Real Estate Investment Trusts in the COVID-19 Era

Rashmi Malhotra

D. K. Malhotra

Abstract

Motivation: This paper carries relevance to the real estate investment community, encompassing investors and REIT managers. It offers valuable insights into the performance of office real estate investment trusts (REITs) during the tumultuous period of the COVID-19 pandemic, shedding light on their relative efficiency.

Premise: This study analyzes the operational efficiency of 20 office REITs from 2018 to 2022, with a particular focus on their adaptability in this challenging landscape brought by the COVID-19 pandemic and resultant surge in vacancy rates and a reduction in rental income.

Approach: This research employs data envelopment analysis (DEA). The application of DEA enables a comprehensive assessment of these REITs' efficiency across a 5-year timeframe.

Results: Findings from this study indicate that the average efficiency score of office REITs declined from 89 percent in 2018 to 87 percent in 2022. Moreover, the number of REITs with a perfect 100 percent efficiency score decreased from 9 to 8 during this period. Through peer analysis, best practices, and potential avenues for efficiency improvement within these REITs were identified.

Conclusion: This research underscores the diminished efficiency in the office real estate market following the onset of the COVID-19 pandemic. These findings empower investors to discern the varying degrees of efficiency among office REITs and make well-informed investment choices. Additionally, REIT managers can employ the efficiency frontier and peer analysis to benchmark their performance and uncover areas for enhancement.

Consistency: This manuscript provides empirically grounded insights into the real estate investment sector, renowned for its inherent risks and uncertainties, thus contributing to a deeper understanding of how businesses adapt and navigate complex economic conditions.

Rashmi Malhotra, PhD, Saint Joseph's University, rmalhotr@sju.edu

D. K. Malhotra, PhD, Thomas Jefferson University, Davinder.Malhotra@Jefferson.edu

Keywords: COVID-19, office real estate market, real estate investment trusts (REITs), data envelopment analysis (DEA), efficiency, pandemic impact, peer analysis, investment decisions, benchmarking, business management, risk, uncertainty

JEL Classification Codes: G12, G14, R33

INTRODUCTION

Office real estate investment trusts (REITs) own and operate income-producing commercial office properties. Investors can purchase shares of an office REIT just like a regular stock, and the REIT generates income from the rent collected on the properties. Office REITs can provide investors with exposure to the commercial real estate market without the need to purchase and manage properties themselves.

The performance of office REITs has been mixed due to the ongoing COVID-19 pandemic and the subsequent impact on the commercial real estate market. Some office REITs with properties in suburban or secondary markets have fared better than those in urban centers, as more people and businesses have moved away from crowded cities. Additionally, some office REITs with properties leased to tenants in essential businesses or industries that were less affected by the pandemic have performed relatively well. With remote work becoming more prevalent, many businesses have decreased their demand for office space. This has led to increased vacancy rates and lower rental income for office REITs. Many companies have delayed their lease renewals as they evaluate their future space needs. This has created uncertainty for office REITs and made it difficult for them to plan. To retain tenants and attract new ones, office REITs had to offer rent concessions, such as rent reductions or rent-free periods. This has led to lower rental income and reduced cash flows for office REITs. According to Akinsomi (2021), the workplace has witnessed a convergence of technological advancements and the influence of the COVID-19 pandemic, resulting in a transformation of occupier behavior, specifically regarding the usage and expected demand for property space in the future. Thus, office REITS need effective decision-making tools to make better decisions.

This study benchmarks the financial performance of office REITs based on the financial ratios computed from their financial statements for the period December 2018 to December 2022. The study is important for several reasons. By comparing the financial performance of office REITs to their peers and the broader market, investors can get a better understanding of how each REIT is performing. This information can be used to make investment decisions and identify potential opportunities.

By analyzing the strategies and practices of top-performing office REITs, investors can learn from their success and potentially apply similar strategies to their own investments. This can help investors improve their own performance and achieve their investment goals.

Benchmarking can provide investors with a better understanding of the office REIT market and its key drivers. Furthermore, by analyzing trends in the office REIT market, investors can gain insights into factors such as changes in office space demand, shifts in tenant preferences, and overall economic conditions. Furthermore, REITs are required by law to distribute at least 90 percent of their taxable income to shareholders in the form of dividends, which can provide a steady stream of income for investors. By studying the financial performance of these REITs, investors can evaluate the stability and growth of rental income streams, which is an essential component of total return for income-oriented investors.

This study is organized along the following lines. The next section discusses relevant previous study on the performance of REITs in general as well as sector specific REITs. *Data Envelopment Analysis Model* discusses the model used in this study, followed by a section discussing the data. The section *Empirical Analysis* presents results, followed by a section that summarizes and concludes the study.

PREVIOUS STUDIES

While several studies have analyzed the performance of real estate investment trusts, we are not aware of any study that specifically focuses on the operating efficiency of office real estate investment trusts. Several recent studies have demonstrated the utility of the non-parametric method known as data envelopment analysis (DEA) in examining various aspects of business organizations. DEA has traditionally been employed to compare the efficiency of homogeneous operational units like sales outlets, utility enterprises, schools, hospitals, prisons, and military operations in contrast to other methodologies. In this section, we evaluate the existing literature that has employed DEA to investigate REITs. The pertinent literature can be categorized into two groups: studies analyzing REITs using data envelopment analysis and those focusing on REIT performance.

Newell and Fischer (2009) explored the role of residential real estate REITs in a REIT portfolio and found that the real estate REITs had poorer risk-adjusted performance and fewer advantages in portfolio diversification. Buttimer, Chen, and Chiang (2012), on the other hand, assessed the performance and market timing skills of equity real estate investment trusts and concluded that the overall equity REITs had some ability to time the housing market. However, they also noted that equity REITs were unable to predict fluctuations in the real estate market.

Malhotra, Malhotra, and Nydick (2023) analyzed the performance of retail real estate investment trusts by benchmarking 21 retail REITs on a quarterly basis from September 2019 to December 2021. The evaluation was based on several key factors, including return on assets, earnings before interest taxes (EBIT), depreciation, and amortization margin, revenue growth per year, capital utilization ratio, and interest cost as a percentage of basic earning power. The study found that only three of the retail REITs consistently performed well compared to their peers. Furthermore, the study also identified a significant decline in return on assets, earnings before interest, taxes, depreciation, and amortization (EBITDA) margin, and revenue growth from March 2020 to June 2020. This decline was observed across the majority of the retail REITs, suggesting a widespread impact on the industry during this time period. In a 2003 study, Lewis, Springer, and Anderson utilized stochastic frontier methods to evaluate the cost efficiency of REIT funds. Subsequently, Anderson, and Springer extended this investigation by developing a framework for selecting and constructing portfolios of REITs based on their operational efficiency and the correlation between their price and net asset value. Anderson, Fok, Springer, and Webb (2002) utilized data envelopment analysis to investigate the technical efficiency and economies of scale for REITs. Through their research, they discovered that REITs were technically inefficient, which was caused by a combination of suboptimal use of inputs and a lack of constant returns to scale. Thus, investigating and developing a model that can evaluate the performance of office REITS can aid investors in making better investment decisions.

DATA ENVELOPMENT ANALYSIS MODEL

Data envelopment analysis (DEA) is a widely used optimization approach that evaluates the effectiveness of different decision-making entities based on their inputs and outputs. By measuring how efficiently a decision-making unit (DMU) uses the accessible assets (inputs) to generate a set of outputs, DEA provides an assessment of the entity's performance. DEA computes efficiency scores by comparing the input and output levels of each DMU and assessing their relative performance. The concept of effectivity or productiveness in DEA is expressed as the ratio of outputs produced relative to inputs used. To compare the relative performance of DMUs, DEA compares a DMU's input and output levels with that of the most productive DMU(s). The most efficient DMU(s) receives a 100% effectiveness rating, and any DMU that has lower input-output ratio scores below 100 percent and is considered inefficient relative to the most efficient DMU(s).

To develop a DEA model, we typically consider n DMUs, m input variables, and r output variables. The model assesses the efficiency of each DMU using inputs and outputs, and compares them to the efficiency of the most efficient DMU(s). This approach enables us to identify inefficient DMUs and suggest ways to improve their performance. Given n DMUs, m inputs, and s outputs:

$j = 1, 2, 3, \ldots, n$

$i = 1, 2, 3, \ldots, m$

$r = 1, 2, 3, \ldots, s$

The DMUs use the variables given below:

$X_{i,j}$ refers to the quantity of input i for the j^{th} decision-making unit

$Y_{r,j}$ refers to the quantity of output r for the j^{th} decision-making unit

u_r refers to weight given to r^{th} output

v_i refers to weight given to i^{th} input

Charnes, Cooper, and Rhodes (1978) allocated the most desirable weights to measure the efficiency of a DMU in DEA. Typically, not all units have equal weights; instead, different weights are assigned to inputs and outputs. The efficiency of a DMU in processing inputs to generate outputs is determined by the ratio of weighted output to weighted input, as shown in Equation (1).

DEA's weighting approach acknowledges that some inputs and outputs may be more important than others and considers their relative significance. By maximizing this ratio, DEA identifies the DMUs that operate at the efficient frontier, indicating optimal use of inputs to generate outputs. DEA's method allows for the identification of the most efficient DMUs (100 percent efficient) and suggests ways to improve their performance.

$$\text{Efficiency} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \tag{1}$$

To determine the weight set that maximizes a DMU's efficiency while restricting the efficiency of other DMUs to a range of 0 and 1, we can use a linear program. This program chooses weights such that only efficient decision-making units receive a rating of 1 or 100 percent efficiency, while less efficient DMUs receive lower scores. This allows us to determine the relative efficiency of a DMU. Relative efficiency in DEA models refers to the comparison of the performance of DMUs relative to each other. Thus, we can assess the efficiency of DMUs by measuring their performance in relation to the best-performing units in the dataset. Further, in DEA, efficiency scores are calculated for each DMU based on their ability to convert inputs into outputs.

In this approach, a single DMU is chosen as the reference unit for the assessment. We solve the model shown in Equation (2) and Equation (3) to determine the efficiency score for each of the remaining DMUs. This method allows for the identification of the most efficient DMUs while considering the different weights assigned to their inputs and outputs. By maximizing the efficiency score of each DMU, we can determine the optimal use of inputs to generate the desired outputs and suggest ways to improve performance.

$$\text{Max } \mathrm{E_o} = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{2}$$

subject to

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \text{ j} = 1,.., \text{n} \tag{3}$$

$u_r \geq \varepsilon$, r = 1,…,s

$v_i \geq \varepsilon$, i = 1,….,m

ε is an infinitesimal or non-Archimedean constant that keeps the weights from disappearing (Charnes et al. 1994).

In Equation (2), the optimal objective function reflects the utility of DMU_0, with a score of 1 indicating 100 percent success and positioning the entity on the efficiency frontier. DMUs that score below 1 are considered inefficient and fall below the performance frontier. To solve Equation (2), each DMU serves as the reference unit for determining the efficiency of other DMUs, leading to a Pareto efficiency estimate when all efficient entities are on the efficiency frontier (Thanassoulis 2001).

To convert the model in Equation (2) and Equation (3) into an equivalent linear program, we can use the restrictions of units (Equation [5]) to normalize the denominator. This allows us to easily generate the DEA model of output maximization that aims to maximize the weighted sum of outputs while limiting the weighted sum of inputs to one. Equation (4) and Equation (5) describe this approach in more detail. By applying these models, we can identify the most efficient DMUs and suggest ways to improve the performance of less efficient units.

$$\max \sum_{r=1}^{s} u_r y_{ro} \tag{4}$$

subject to

$$\sum_{i=1}^{m} v_i x_{io} = 1, \tag{5}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \quad \leq 0,\ j = 1,..,n,$$

$$u_r \geq \varepsilon,\ r = 1,\ldots,s$$

$$v_i \geq \varepsilon,\ i = 1,\ldots.,m$$

We use the Charnes, Cooper, and Rhodes (CCR) model in this case. A generic input minimization CCR model, on the other hand, may be written as specified in Equation (6).

$$\min \sum_{i=1}^{m} v'_i x_{io} \tag{6}$$

subject to

$$\sum_{r=1}^{s} u'_r y_{ro} = 1$$

$$\sum_{r=1}^{s} u'_r y_{rj} - \sum_{i=1}^{m} v'_i x_{ij} \quad \leq 0,\ j = 1,..,n, \tag{7}$$

$$u_r \geq \varepsilon,\ r = 1,\ldots,s$$

$$v_i \geq \varepsilon,\ i = 1,\ldots.,m$$

According to the fundamentals of linear programming, every linear program has a related linear program known as its dual. As a result, Equation (8) depicts the dual maximization of DEA program output:

$$\theta^* = \min \theta \tag{8}$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io,}\ i = 1, \ldots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro},\ r = 1, \ldots, s \tag{9}$$

$$\lambda_j \geq 0,$$

θ is unrestricted

If $\theta^* = 1$, the present input levels cannot be lowered, suggesting that the o^{th} decision making unit is on the efficiency frontier. Otherwise, if $\theta^* < 1$, then the efficiency frontier dominates the o^{th} decision making unit. The efficiency level θ^* indicates the o^{th} decision making unit's input-oriented efficiency score. Further, an individual DMU's input decrease is referred to as slack value. A model may have slack for input as well as output; see Equation (10).

$$s_i^- = \theta^* x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \quad i = 1, \ldots, m$$

$$s_r^+ = \sum_{j=1}^{n} \lambda_j y_{rj} - y_{ro},\ r = 1, \ldots, s \tag{10}$$

We solve the following linear program specified in Equation (11) to discover any non-zero slacks after implementing the linear program per Equation (10).

$$\max \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta^* x_{io,}\ i = 1, \ldots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro},\ r = 1, \ldots, s \tag{11}$$

$$\lambda_j \geq 0$$

θ is unrestricted

For all i and r, a decision-making unit is efficient if and only if $\theta^* = 1$ and $s_i^{-*} = s_r^{+*} = 0$. A decision-making unit is inefficient if and only if $\theta^* = 1$ and $s_i^{-*} \neq 0$ and (or) $s_r^{+*} \neq 0$ for some i and r. Models (8) and (11), in fact, form a two-stage DEA process that describes the DEA model below:

$$\min \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io}, \; i = 1,\ldots,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}, \; r = 1,\ldots,s \tag{12}$$

$$\lambda_j \geq 0$$

θ is unrestricted

In addition to identifying efficient entities by using them as "role models," DEA also enables us to uncover the underlying causes of sub-optimal performance. This allows investors to make informed decisions about whether to invest in a specific asset management company and empowers managers to pinpoint areas that require improvement. The term *relative productivity* is used in DEA to encourage firms to compare themselves with other recognized productive organizations.

One key feature of the DEA model is the establishment of an efficiency frontier of efficient businesses that serves as a benchmark for comparison with the decision-making unit being evaluated. DMUs that fall below this frontier must enhance one of their input values without adversely affecting the others in order to achieve efficiency. By using DEA, managers can identify and address inefficiencies in their operations and improve their overall performance.

DATA

To assess the relative efficiency of each real estate investment trust (REIT), we utilize the data envelopment analysis (DEA) model. The assessment relied on annual data sourced from Standard & Poor Net Advantage, spanning from December 2018 to December 2022. This time period allows us to examine the performance of office REITs before the pandemic, during the pandemic, and in the post-vaccination period, providing insights into their performance across these distinct periods. In our study, we analyze the financial performance of 21 office REITs. This analysis involves scrutinizing six different financial metrics obtained from their balance sheets and income statements. By examining these metrics, we aimed to gain insights into the financial performance of the office REITs under study. These metrics are return on assets (ROA), gross margin, total revenue growth over the previous year, debt-to-equity ratio, capital intensity or capital efficiency ratio, and net debt to earnings before interest and taxes (EBIT) ratio. ROA, gross margin, and total revenue growth over the previous year are all indicators of a REIT's profitability and efficiency in generating income from its real estate assets. These ratios can determine if a REIT is effectively utilizing its assets to generate income and if its operations are sustainable over the long term.

The debt-to-equity ratio, net debt to EBIT ratio, and capital efficiency ratio are all measures of a REIT's financial risk and leverage. These ratios can be used to evaluate the REIT's ability to manage its debt and meet its financial obligations, as well as assess the level of financial risk associated with investing in the REIT.

Overall, these financial ratios can provide valuable insights into the operating efficiency, financial health, and performance of office REITs that, in turn, can help inform investment decisions and portfolio management strategies. The combination of these metrics allowed us to gain a comprehensive understanding of each REIT's financial health and operational efficiency. The DEA model provides an overall efficiency score for each company, allowing us to compare the performance of the most and least efficient REITs. By examining these six financial measures in the DEA model, we can provide a comprehensive evaluation of the office real estate investment trusts' performance.

ROA is used to evaluate the operating efficiency of a REIT because it provides insights into how effectively the REIT generates returns from its invested assets. ROA is calculated by dividing the net income of the REIT by its total assets. A higher ROA indicates that the REIT is effectively utilizing its assets to generate income, demonstrating operational efficiency. On the other hand, a lower ROA suggests that the REIT may not be maximizing its asset utilization and should improve its operational performance.

ROA is particularly relevant for evaluating the operating efficiency of a REIT because the real estate sector is asset-intensive. The performance of a REIT heavily relies on effectively managing and generating income from its real estate assets, such as office buildings, commercial properties, or residential complexes. Therefore, ROA provides a key metric for investors, analysts, and stakeholders to gauge how efficiently the REIT is utilizing its assets to generate profits and measure its operational efficiency.

Gross margin is a financial metric that represents the difference between a company's revenue and its cost of goods sold (COGS). It is usually expressed as a percentage and indicates the amount of money a company makes from sales after deducting the costs associated with producing and selling products or services. By examining the gross margin, we can assess the REIT's ability to generate revenue after deducting the direct costs associated with its operations. A higher gross margin indicates that the REIT has better control over its costs and is able to generate a higher proportion of revenue as profit. This suggests effective cost management and operational efficiency. Additionally, gross margin levels help identify trends in the REIT's profitability over time. If the gross margin increases, it indicates that the REIT is improving its cost efficiency or successfully increasing its pricing power. Conversely, a declining gross margin may indicate challenges in cost control or pricing pressures.

Total revenue growth over the previous year is a financial measure that compares a company's total revenue in the current year with that of the previous year. Total revenue growth is used to evaluate the company's ability to increase sales and generate more revenue over time. Steady or increasing revenue growth is an important indicator of a REIT's ability to generate sustainable income. It demonstrates that the REIT is successfully attracting tenants, maintaining occupancy rates, implementing effective leasing strategies, and potentially achieving rent increases.

The debt-to-equity ratio is used to evaluate the operating efficiency of a REIT because it provides insights into the REIT's leverage position and financial stability. The debt-to-equity ratio is calculated by dividing the total debt of the

REIT by its shareholder equity. Evaluating the debt-to-equity ratio is crucial for assessing the operating efficiency of a REIT because this gauges the financial health and stability of a REIT. A REIT with a healthier debt-to-equity ratio may have better access to financing, lower interest expenses, and greater flexibility in pursuing growth opportunities. In contrast, a higher debt-to-equity ratio could pose challenges for the REIT, impacting its ability to invest, generate returns, and maintain stability in adverse market conditions.

Net debt as a percentage of EBIT is a financial ratio that measures a company's ability to pay off the debt using earnings. The ratio is calculated by dividing a company's net debt (total debt minus cash and cash equivalents) by the EBIT. This metric evaluates a company's financial leverage and the subsequent ability to service debt obligations. A higher net debt to EBIT ratio indicates that the company has a higher debt burden relative to the earnings, leading to increased financial risk and enhanced vulnerability to economic downturns. Conversely, a lower ratio suggests that the company has a stronger ability to service debt and is generally considered more financially stable. Evaluating net debt as a percentage of EBIT helps assess the operating efficiency of a REIT by considering its ability to generate earnings that are sufficient to cover its debt obligations. EBIT provides insights into the REIT's financial health, risk profile, and ability to manage its debt load effectively.

The capital intensity ratio is a financial metric that measures a company's level of capital investment relative to revenue. The ratio is calculated by dividing a company's total capital expenditures by total revenue. This metric evaluates a company's capital efficiency and revenue generation capability using the invested capital. A higher capital intensity ratio indicates that the company has higher capital requirements to generate revenue that may limit growth prospects or result in lower profitability. Conversely, a lower ratio suggests that the company can generate revenue with a lower level of capital investment leading to higher profitability and growth potential. The capital intensity ratio is often used by investors and analysts to assess a company's operational efficiency and use of capital.

Table 1 provides a summary statistic of the data used in this study. Table 1 shows the impact of COVID-19 induced lockdowns on office REITs. The return on assets for office REITs declined from 1.7 percent in 2018 to 1.2 percent in 2020, rose to 1.4 percent in 2022. Gross margin declines from 62.5 percent in 2018 to 60.7 percent in 2020. Gross margin dipped further to 60 percent in 2022 as we deal with post-pandemic business model in which there is less demand for office space due to acceptance of work from home as a new normal. Capital intensity ratio that measures the amount of capital required per dollar sales revenue increased to 9.53 in 2020 relative to 8.91 in 2018 that points to decline in capital utilization efficiency for office REITs. Total revenue growth over the previous year became negative at –6.2 percent in 2020 relative to 2019. Average revenue growth increased by 6 percent in 2022. Office REITs have more debt on their balance sheet. Debt-to-equity ratio, on average, has worsened from 1.062 in 2018 to 1.17 in 2022. Net debt to EBIT ratio has also worsened for office REITs from 8.38 in 2018 to 9.48 in 2020. In 2022, on average, net debt to EBIT ratio was 8.84.

TABLE 1. Summary Statistics of the Variables Used in This Study

Year	Return on Assets (%)	Gross Margin (%)	Capital Intensity Ratio	Total Revenue Growth (%)	Debt/Equity Ratio	Net Debt/EBIT Ratio
2018	1.7	62.5	8.9	2.4	1.1	8.4
2019	1.6	61.7	8.7	7.8	1.0	7.8
2020	1.2	60.7	9.5	-6.2	1.0	9.5
2021	1.3	60.8	9.5	2.4	1.1	8.9
2022	1.4	60.0	9.2	6.0	1.2	8.8

EMPIRICAL ANALYSIS

Using the data envelopment analysis (DEA) method, we evaluated and compared the operating efficiency of 21 office real estate investment trusts (REITs). Our assessment involved rating each REIT's efficiency on a scale of 1 to 100, using annual data from 2018 to 2022. The efficiency scores of the 21 REITs analyzed are summarized in Table 2. Using DEA, we compare their performance and assess their efficiency, ultimately identifying the most efficient REITs. This approach provides valuable insights into the relative efficiency of different organizations and can be a powerful decision-making tool across various industries. Based on our analysis, we can make informed decisions on better-performing REITs to invest in or recommend to others.

According to Table 2, we observed that, on average, five office REITs demonstrated 100 percent efficiency relative to their peers from 2018 to 2022. These REITs are ARE, CUZ, HIW, OFC, and OPI. Additionally, BXP, KRC, DEA, PDM, FSP, and CMCT are also relatively efficient, with efficiency scores over 90 percent. Conversely, VRE had the lowest average efficiency score among office REITs, with a score of 54 percent, followed by SLG with an efficiency score of 63 percent.

As shown in Table 2, the average efficiency score of office REITs has decreased from 89 percent in 2018 to 87 percent in 2022. In 2018, 9 out of 21 office REITs achieved 100 percent efficiency that declined to 6 out of 21 in 2020. However, in 2022, the number of office REITs achieving 100 percent efficiency increased to 8. Specifically, ARE, BXP, KRC, CUZ, HIW, OFC, and OPI are 100 percent efficient relative to their peers in 2022.

Based on their efficiency scores, we ranked the office REITs as shown in Table 3. The rankings of office REITs varied on a yearly basis, except for CUZ, ARE, HIW, OFC, and OPI that consistently outperformed their peers throughout the sample period. The remaining office REITs continued to climb the rankings each year. The considerable variation in efficiency scores among the different real estate investment trusts highlights the varying degrees of management skill, with some REITs performing significantly better than others.

To further assess the efficiency of office REITs, we calculated a performance index for each REIT. We calculated the index was calculated by dividing the standard deviation of efficiency scores over the sample period of 2018 to 2022 by the average efficiency score. The office REIT with the lowest performance index score was deemed the most efficient, having the lowest coefficient of variation in efficiency scores per unit of efficiency score. Table 4 provides a

TABLE 2. Efficiency Scores of Office REITs

Efficiency scores are based on return on assets (%), gross margin (%), annual revenue growth over previous year (%), capital efficiency ratio, debt-to-equity ratio, and net debt as a percentage of EBIT.

Company	2018	2019	2020	2021	2022	Average per Office REIT
ARE	100%	100%	100%	100%	100%	100%
BXP	100%	100%	85%	100%	100%	97%
KRC	100%	83%	90%	100%	100%	94%
VNO	84%	84%	72%	71%	74%	77%
CUZ	100%	100%	100%	100%	100%	100%
HIW	100%	100%	100%	100%	100%	100%
OFC	100%	100%	100%	100%	100%	100%
DEI	82%	79%	70%	73%	81%	77%
SLG	71%	71%	68%	55%	50%	63%
JBGS	100%	100%	94%	74%	70%	87%
VRE	53%	52%	49%	51%	63%	54%
HPP	83%	83%	79%	86%	80%	82%
DEA	100%	88%	93%	100%	91%	94%
PGRE	66%	69%	71%	70%	68%	69%
PDM	89%	100%	100%	96%	96%	96%
BDN	87%	89%	89%	83%	85%	87%
KBSR	86%	80%	81%	80%	80%	81%
OPI	100%	100%	100%	100%	100%	100%
FSP	88%	89%	92%	100%	98%	93%
CMCT	96%	100%	81%	100%	100%	95%
Average per year	89%	88%	86%	87%	87%	

summary of rankings for REITs based on their performance index from 2018 to 2022. Based on the mean efficiency score and standard deviation, we computed the performance index for each office REIT as the standard deviation divided by the mean efficiency score. The index was calculated by dividing the standard deviation of efficiency scores over the sample period of 2018 to 2022 by the average efficiency score. A lower score indicates that the REIT has a lower risk per unit of efficiency score.

Based on the performance index, the most efficient office REITs have been ARE, CUZ, HIW, OFC, and OPI, with a performance index score of 0. This indicates that they have consistently performed at 100 percent efficiency in comparison to their peers. On the other hand, JBGS is the least efficient office REIT with a performance index of 0.17, followed by SLG, which has a score of 0.16.

In addition to the efficiency scores and performance index, we constructed an efficiency frontier for office REITs based on their efficiency scores in the year 2022. The efficiency frontier is a graphical representation of the best possible performance of a group of entities, in this case, office REITs, given their inputs and outputs. The performance index enables investors to identify the most efficient entities in the group and the potential areas for improvement for less efficient entities.

TABLE 3. Ranking Office REITs Based on Their Efficiency Score from 2018–2022

Efficiency scores are based on return on assets (%), gross margin (%), annual revenue growth over previous year (%), capital efficiency ratio, debt-to-equity ratio, and net debt as a percentage of EBIT.

Company	2018	Company	2019	Company	2020	Company	2021	Company	2022
CUZ	100%	CUZ	100%	CUZ	100%	KRC	100%	CUZ	100%
DEA	100%	OFC	100%	ARE	100%	CUZ	100%	CMCT	100%
HIW	100%	JBGS	100%	PDM	100%	HIW	100%	ARE	100%
ARE	100%	PDM	100%	OPI	100%	FSP	100%	HIW	100%
JBGS	100%	ARE	100%	HIW	100%	ARE	100%	OFC	100%
KRC	100%	HIW	100%	OFC	100%	DEA	100%	KRC	100%
OPI	100%	OPI	100%	JBGS	94%	OPI	100%	OPI	100%
OFC	100%	CMCT	100%	DEA	93%	OFC	100%	BXP	100%
BXP	100%	BXP	100%	FSP	92%	CMCT	100%	FSP	98%
CMCT	96%	FSP	89%	KRC	90%	BXP	100%	PDM	96%
PDM	89%	BDN	89%	BDN	89%	PDM	96%	DEA	91%
FSP	88%	DEA	88%	BXP	85%	HPP	86%	BDN	85%
BDN	87%	VNO	84%	CMCT	81%	BDN	83%	DEI	81%
KBSR	86%	KRC	83%	KBSR	81%	KBSR	80%	HPP	80%
VNO	84%	HPP	83%	HPP	79%	JBGS	74%	KBSR	80%
HPP	83%	KBSR	80%	VNO	72%	DEI	73%	VNO	74%
DEI	82%	DEI	79%	PGRE	71%	VNO	71%	JBGS	70%
SLG	71%	SLG	71%	DEI	70%	PGRE	70%	PGRE	68%
PGRE	66%	PGRE	69%	SLG	68%	SLG	55%	VRE	63%
VRE	53%	VRE	52%	VRE	49%	VRE	51%	SLG	50%

Figure 1 presents the efficiency frontier for office REITs in 2022. The frontier depicts the maximum efficiency that can be achieved by office REITs for a given level of inputs. In other words, the efficiency frontier shows the boundary of what is feasible for office REITs using their input-output relationship. Office REITs that fall on or near the efficiency frontier are considered the most efficient, while those that fall below the frontier have room for improvement by reducing the input use or increasing the output.

The efficiency frontier in Figure 1 shows that the most efficient office REITs in 2022 were ARE, CUZ, HIW, OFC, and OPI, with a perfect efficiency score of 100. These REITs were located on the frontier, indicating that they achieved the highest level of output with the least amount of input compared to their peers. On the other hand, REITs such as VRE, SLG, and JBGS were below the efficiency frontier, indicating that they could improve their efficiency by reducing their input use or increasing their output.

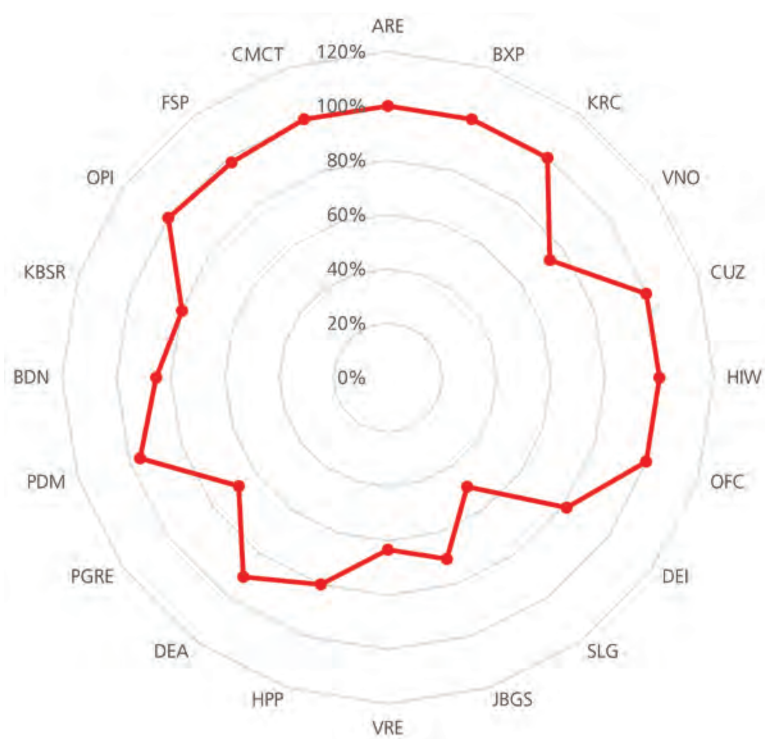
The figure also shows that VRE, SLG, JBGS, and PDM were the most inefficient REITs, located below the efficiency frontier. These REITs can learn from their more efficient peers and strive to improve their efficiency to move closer to the efficiency frontier. By analyzing the efficiency frontier, we can identify the REITs not performing as well as their peers and may require further analysis and attention from investors and managers.

TABLE 4. Performance Index of 20 Office REITs

Index is computed by dividing the standard deviation of the efficiency scores over the sample period of 2018 to 2022 by the average efficiency score. Lower the score means that the REIT has lower risk per unit of efficiency score.

Company	Average	Std. Dev.	Performance Index
ARE	100%	0.00%	0.00
BXP	97%	6.56%	0.07
KRC	94%	7.95%	0.08
VNO	77%	6.49%	0.08
CUZ	100%	0.00%	0.00
HIW	100%	0.00%	0.00
OFC	100%	0.00%	0.00
DEI	77%	5.25%	0.07
SLG	63%	10.02%	0.16
JBGS	87%	14.49%	0.17
VRE	54%	5.57%	0.10
HPP	82%	2.65%	0.03
DEA	94%	5.60%	0.06
PGRE	69%	1.96%	0.03
PDM	96%	4.38%	0.05
BDN	87%	2.42%	0.03
KBSR	81%	2.76%	0.03
OPI	100%	0.00%	0.00
FSP	93%	5.34%	0.06
CMCT	95%	8.10%	0.08

FIGURE 1. Efficiency Frontier of Office Real Estate Investment Trusts for the Year 2022



The identification of efficient and inefficient REITs is crucial for investors so as to make informed decisions when allocating their investments. By investing in more efficient REITs, investors can potentially earn higher returns while reducing risk. Furthermore, REIT managers can use this information to benchmark their performance against their peers and identify areas where they can improve their efficiency.

To determine the relative performance of inefficient office REITs, we conducted a peer analysis, a crucial aspect of benchmarking using DEA. This analysis allowed us to compare the performance of various office REITs against their peers, thereby enabling us to identify the underperforming units and the related contributing factors. Moreover, the peer analysis facilitated the identification of best practices and areas for improvement, while also uncovering trends and patterns in the REIT sector's overall performance. Specifically, we computed the peers for inefficient REITs for the year 2022.

Table 5 illustrates the analysis based on six key performance indicators—return on investment (ROA), gross margin, revenue growth compared to the previous year, capital efficiency ratio, debt-to-equity ratio, and net debt to EBIT ratio for the REIT named OPI. OPI serves as a benchmark or peer for 12 inefficient REITs in December 2022, implying that the 12 inefficient REITs should emulate the best practices of OPI to improve their performance to improve their efficiency. Table 5 also shows that CUZ serves as a peer for 6 inefficient REITs, OFC is a peer for 4 REITs, KRC for 3, and ARE is a peer for 2 REITs.

Peer analysis helps determine the closest and farthest peers for inefficient REITs. In DEA, determining the peers for an inefficient DMU involves identifying efficient units that can serve as benchmarks for evaluating and improving the efficiency of the inefficient DMU. The peers are used as reference points to understand how the inefficient DMU can improve its performance. By comparing the inefficient DMU's input-output levels and performance to those of the

TABLE 5. Peer Companies and Their Weights in Percentage

This table shows those office real estate investment trusts that can serve as a benchmark for office REITs with DEA efficiency score of less than 100. Peer analysis is based on end of December 2022.

Company	Efficiency	ARE	KRC	CUZ	HIW	OFC	OPI	CMCT	Sum
VNO	74%	0.00	0.00	0.00	0.00	0.28	0.19	0.53	1.00
DEI	81%	0.00	0.15	0.16	0.00	0.00	0.35	0.35	1.00
SLG	50%	0.00	0.00	0.30	0.00	0.00	0.09	0.61	1.00
JBGS	70%	0.01	0.00	0.15	0.00	0.00	0.00	0.84	1.00
VRE	63%	0.00	0.00	0.27	0.00	0.00	0.08	0.65	1.00
HPP	80%	0.00	0.10	0.00	0.47	0.00	0.00	0.43	1.00
DEA	91%	0.00	0.35	0.19	0.04	0.00	0.19	0.22	1.00
PGRE	68%	0.00	0.00	0.56	0.00	0.00	0.05	0.38	1.00
PDM	96%	0.00	0.00	0.00	0.00	0.08	0.35	0.56	1.00
BDN	85%	0.00	0.00	0.00	0.00	0.10	0.35	0.55	1.00
KBSR	80%	0.00	0.00	0.00	0.00	0.91	0.09	0.00	1.00
FSP	98%	0.18	0.00	0.00	0.00	0.00	0.00	0.82	1.00

efficient peers, the DMUs can identify areas of inefficiency and opportunities for improvement can be identified. The inefficient DMU can analyze the practices, strategies, and resource allocations of its peers to learn from their efficient operations and implement changes to enhance its own efficiency. For example, JBGS should adopt 84 percent of CMCT's best practices. Likewise, FSP must adopt CMCT's (82 percent) and ARE's (16 percent) best practices. CMCT is FSP's closest peer with a weight of 82 percent. Among these 12 inefficient REITs, CMCT is the lead peer for JBGS (84 percent), FSP (82 percent), VRE (65 percent), SLG (61 percent), PDM (55 percent), and VNO (53 percent), but the least with KBSR (0 percent). Inefficient REITs can learn from CMCT's performance and aim to achieve similar efficiency to reach 100 percent efficiency. Table 5 also shows that OPI is the peer for VNO (19 percent), DEI (35 percent), SLG (9 percent), VR (8 percent), DEA (19 percent), PGRE (5 percent), PDM (35 percent, and KBSR (9 percent). This is crucial because by identifying the industry's most efficient peers, inefficient office REITs can take necessary steps to improve their performance by studying their peers' practices and strategies and implementing similar measures. This can improve their overall performance, making them more competitive thereby attracting more investment, ultimately increasing returns for shareholders. This exercise underscores the importance of identifying efficient peers and learning from them for the growth and success of retail REITs.

The efficient companies in the study had a comparable mix of inputs and outputs to the inefficient company, but they performed at a higher standard, producing more. These efficient peers offer the inefficient company a chance to learn and improve by serving as ideal models to follow to enhance performance. The similarity of inputs and outputs at a higher level shows the potential for the inefficient company to make improvements and achieve a similar level of efficiency.

Once the inefficient REITs were identified, we should also determine the specific areas where they were falling behind their efficient peers. This information enables the inefficient REITs to focus their efforts on improving their performance in these specific areas. To determine these areas, we calculated slack variables that give a measure of the amount by which a given performance metric falls short of the benchmark.

Table 6 presents an overview of the slack variables for the inefficient REITs for the year 2022. The slack variables serve as a measure of how far behind the benchmark the performance of the inefficient REITs falls in various areas. The table highlights the areas where the inefficient REITs need to focus their attention in order to move closer to the efficiency frontier. This information can be used to set specific goals, prioritize initiatives, and allocate resources effectively in order to achieve better performance and maximize returns for shareholders.

Table 6 reveals the specific areas where several inefficient (REITs) need improvement. All 12 inefficient REITs should improve their debt-to-equity ratio and net debt to EBIT ratio. Meanwhile, VNO, SLG, JBSG, VRE, PGRE, PDM, BDN, KBSR, and FSP should also concentrate their efforts on enhancing their total revenue growth over the previous year. By focusing on these areas, these inefficient REITs can take the necessary steps to improve their performance and reach their full potential.

TABLE 6. Slack Variables for Inefficient Office Real Estate Investment Trusts for December 2022

This table shows the areas in which inefficient office real estate investment trusts are lagging relative to efficient peers.

Company	Efficiency	Capital Intensity Ratio	Debt/Equity Ratio	Net Debt/EBIT Ratio	Return on Assets %	Gross Margin %	Total Revenue Growth (%)
VNO	74%	0.000	0.888	3.369	0.000	0.000	0.032
DEI	81%	0.000	0.701	3.609	0.000	0.000	0.000
SLG	50%	0.000	0.766	12.987	0.000	0.000	0.117
JBGS	70%	0.000	0.249	5.245	0.000	0.000	0.095
VRE	63%	0.000	0.481	8.867	0.000	0.000	0.025
HPP	80%	0.000	0.778	4.472	0.000	0.000	0.000
DEA	91%	0.000	0.416	2.834	0.000	0.000	0.000
PGRE	68%	0.000	0.357	6.081	0.000	0.000	0.091
PDM	96%	0.000	0.242	3.509	0.000	0.000	0.076
BDN	85%	0.000	0.689	3.483	0.000	0.000	0.104
KBSR	80%	0.000	2.809	6.446	0.000	0.000	0.185
FSP	98%	0.000	0.008	1.472	0.000	0.000	0.337

SUMMARY AND CONCLUSIONS

The COVID-19 pandemic has had varying effects on office real estate investment trusts (REITs) as remote work has decreased the demand for office space, resulting in higher vacancy rates and reduced rental income. To retain and attract tenants, office REITs had to offer rent concessions that had a negative impact on rental income and cash flows. As more businesses have adopted hybrid work models, flexible office spaces such as co-working spaces have become more popular, posing a competitive threat to traditional office REITs. By comparing office REITs against benchmarks, investors and other stakeholders can gain valuable insights into performance, identify best practices, manage risks, and better understand the market and its key drivers.

Using the data envelopment analysis (DEA) method, we evaluated and compared the efficiency of 21 office REITs from 2018 to 2022. The efficiency scores ranged from 54 percent to 100 percent, with the most efficient REITs consistently outperforming their peers. ARE, CUZ, HIW, OFC, and OPI were the top five most efficient REITs.

The average efficiency score of office REITs decreased from 89 percent in 2018 to 87 percent in 2022, and the number of 100 percent efficient REITs decreased from 9 to 8 during this time. Rankings of office REITs based on efficiency scores and performance index varied annually, emphasizing the importance of management skill in the sector.

CUZ, CMCT, ARE, HIW, OFC, KRC, OPI, and BXP dominated the efficiency frontier for office REITs in 2022, serving as benchmarks for other REITs to improve their performance. We conducted peer analysis to identify best practices and potential areas for improvement, with OPI serving as a benchmark or peer for 12 inefficient REITs in December 2022. Other efficient REITs also served as peers for less efficient ones, providing a basis for comparison and improvement.

Investors can utilize our findings to evaluate the relative efficiency of different REITs in the industry and make informed investment decisions. Additionally, REIT managers can use the efficiency frontier and peer analysis to benchmark their performance and identify areas for improvement.

Hybrid work models and flexible office spaces have significant implications for office REITs, posing a competitive threat to traditional models. REIT managers must consider evolving tenant needs, adapt offerings, and align with the demand for flexibility. The fluctuating rankings of office REITs emphasize the importance of management expertise. Strategies should be continuously evaluated and adjusted to navigate the post-COVID office market, while adopting innovative approaches, optimizing efficiency, and effectively managing tenant relationships to improve performance.

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The Impact of Generative AI on Employment and Labor Productivity

Jason Yu

Cheryl Qi

Abstract

Motivation: After the recent introduction of ChatGPT, the rise of generative artificial intelligence (GAI) has ignited discussions about its potential to disrupt employment and impact labor productivity. Our paper empirically examines the potential effects of GAI.

Premise: Our paper showcases GAI's impact on employment and labor productivity in the United States.

Approach: We investigate the 100 largest publicly traded U.S. companies. The key variable of GAI exposure is from Eisfeldt, Schubert, and Zhang (2023). Employment is measured by the number of employees or the number of employees scaled by total assets. Labor productivity is assessed using real sales per employee or operating income per employee. We employ a difference-in-differences methodology, comparing changes in firms with high GAI exposure to those with low GAI exposure, before and after the launch of ChatGPT.

Results: Our findings indicate that the introduction of GAI has not had a negative impact on employment. Furthermore, GAI has created positive and statistically significant effects on labor productivity.

Conclusion: We conclude that GAI has not decreased employment but has increased labor productivity. The impact of GAI extends beyond the business world. Our discovery highlights the revolutionary potential of GAI and encourages policy makers to utilize it to benefit and advance society.

Consistency: Our research provides the latest empirical evidence on GAI's impact on employment and labor productivity. The findings suggest that GAI's adoption enhances labor productivity for businesses and creates employment stability. Our discovery has prevalent and profound influence on the present and future of our world.

Jason Yu, Livingston High School, jasony.livingston@gmail.com

Cheryl Qi, PhD, University of Ottawa, Qianru.Qi@telfer.uOttawa.ca

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Keywords: artificial intelligence, generative artificial intelligence, employment, labor productivity, industrial advancement, science and technology, society, large language model, machine learning, generative pre-trained transformer

JEL Classification Codes: J21, J24, O33

INTRODUCTION

ChatGPT, an artificial intelligence (AI) chatbot launched by OpenAI Inc. on November 30, 2022, represents one of the most advanced AIs to date. This tool signifies the recent rapid development of generative artificial intelligence (GAI). GAI employs neural networks and machine learning algorithms to generate text and code, mimicking human creativity. GAI has applications in various fields, including creative content generation and even the automation of tasks that require human-like decision-making and creativity. Due to these automations, GAI has raised concerns about its potential impact on the labor market and ignited excitement about its potential influence on labor productivity. In particular, some economists are worried that GAI may replace existing employment. For instance, Goldman Sachs economists believe that generative AI could potentially replace up to one-fourth of current jobs globally, amounting to 300 million jobs.[1] The McKinsey Global Institute estimates that GAI will lead to the automation of 30 percent of the hours worked today by 2030.[2] However, it is an empirical question whether this concern is warranted.

Some people are excited about GAI's influence on labor productivity. For example, Goldman Sachs economists believe GAI could boost global productivity growth by 1.5 percent over a 10-year period. McKinsey Global Institute estimates that GAI has the potential to increase U.S. labor productivity by 0.5 to 0.9 percentage points annually through 2030. Combining GAI and all other automation could help U.S. productivity grow 3 to 4 percent annually. However, some other economists caution that we need to be realistic about GAI's economic impacts. For example, Carlsson-Szlezak et al. comment that technology's impact on productivity growth has been consistently overstated.[3] These different views beg the empirical question: Is there any impact of GAI on labor productivity growth?

In this paper, we address these questions using the most recent data. In particular, we analyze the impact of ChatGPT on employment and labor productivity of the 100 largest U.S. publicly traded companies. Specifically, we examine how exposure to GAI affects employment and revenue productivity in nine months after the launch of ChatGPT. We find no evidence of employment declines, but significant productivity increases for firms more exposed to GAI. These findings suggest that the industrial advancement represented by GAI has a positive impact on labor productivity.

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[1]Source: https://www.goldmansachs.com/intelligence/pages/generative-ai-could-raise-global-gdp-by-7-percent.html, visited on 9/21/2023.

[2]Source: https://www.mckinsey.com/mgi/our-research/generative-ai-and-the-future-of-work-in-america#/, visited on 9/23/2023.

[3]Source: https://www.weforum.org/agenda/2023/08/generative-ai-realistic-economic-impact/, visited on 10/1/2023.

LITERATURE REVIEW, BACKGROUND INFORMATION, AND HYPOTHESIS DEVELOPMENT

The existing academic literature has extensively focused on the potential for automation and artificial intelligence (AI) technologies to replace human labor and reduce employment. For instance, Acemoglu and Restrepo (2020) investigated the use of industrial robots in local labor markets in the United States from 1990 to 2007. Their findings revealed that an additional robot per thousand workers was associated with a 0.18 to 0.34 percent decrease in the employment-to-population ratio and a decrease in wages ranging from 0.25 to 0.5 percent. In a more recent study, Acemoglu and Restrepo (2022) revealed that approximately 50 to 70 percent of changes in the wage structure over the past four decades can be attributed to declining wages for employees in routine jobs within rapidly automating industries.

However, Dauth et al. (2021) examined how local labor markets in Germany adapted to the presence of industrial robots. Their research indicated that exposure to robots led to displacement effects in the manufacturing sector, which were counterbalanced by the creation of new jobs in the services sector. Within firms, automation was associated with greater job stability for existing employees, as they assumed new responsibilities within their respective companies.

It's important to note that these studies were conducted prior to the emergence of generative artificial intelligence (GAI). Consequently, there is limited empirical knowledge regarding the impact of more advanced GAI systems capable of performing a wider range of tasks across various occupations and industries. GAI is a general term describing machine learning applications trained on large amounts of data to generate output based on prompts (Satra 2023). An example of GAI is the generative pre-trained transformer (GPT), which uses large language models (LLMs) to process images and natural languages to produce text outputs. GPT-4 has demonstrated human-level performance, such as scoring in the top 10 percent of test takers on a simulated bar exam (OpenAI 2023). In a broader sense, LLMs have a wide range of applications, including generating text, images, videos, programming code, protein sequences, games, and essentially any task that can be performed by computers (Satra 2023; Eloundou et al. 2023).

Eisfeldt, Schubert, and Zhang (2023) have conducted an analysis of the relationship between GAI and firm values. Their findings reveal that firms with high exposure to GAI experience a 0.4 percent increase in daily excess returns compared to those with lower exposures, particularly following the release of ChatGPT. They also find that companies with higher GAI exposure experience higher stock return volatility after the release of ChatGPT. In a separate study, Eloundou et al. (2023) emphasize that LLMs have the potential to influence at least 10 percent of work tasks for approximately 80 percent of the U.S. workforce. However, we haven't found any academic research publication that examines the impact of GAI on employment and labor productivity at the firm level.

As mentioned earlier, Goldman Sachs economists speculate that GAI could potentially replace 300 million jobs. According to the McKinsey Global Institute, they project that GAI may automate up to 30 percent of work hours by 2030. These conjectures align with the findings of Acemoglu and Restrepo

(2020) regarding industrial robots. However, it's worth noting that Dauth et al. (2021) report a different perspective, suggesting that automation was linked to increased job stability for current employees within German firms. These varying viewpoints and research findings give rise to the following hypothesis.

Hypothesis 1: The introduction of GAI tools will have a negative impact on employment levels across companies, especially those with higher levels of GAI exposure.

It is natural to expect that GAI tools can enhance worker efficiency. Noy and Zhang (2023) examined 444 college-educated professionals and reported that ChatGPT improved productivity, specifically in mid-level professional writing tasks, in an online experimental setting. Brynjolfsson, Li, and Raymond (2023) explored the influence of GAI on 5,179 customer support agents in a Fortune 500 software firm and found a 14 percent increase in productivity, with a greater impact on low-skilled workers. They also found that AI assistance improves employee retention. As highlighted by Noy and Zhang (2023), their experiment primarily captures the direct and immediate effects of ChatGPT on the selected tasks. The impacts of GAI can be multifaceted and task-dependent. Extrapolating to a broader context, we conjecture that GAI will have a positive impact on overall worker productivity, as proxied by financial measures such as sales per employee and operating income per employee. This leads to the second hypothesis.

Hypothesis 2: The introduction of GAI tools will have a positive impact on labor productivity across companies, especially those with higher levels of GAI exposure.

DATA COLLECTION

We adopt the variables of *generative AI exposure* and industry *sector* from Eisfeldt, Schubert, and Zhang (2023). In particular, Table C8 of their paper lists the generative AI exposure scores for the largest 100 public companies with headquarters in the United States. The authors calculate a company's labor exposure to GAI by first measuring each occupation's exposure to GAI and then aggregating the occupational level to company level. In addition, we collect number of employees and other financial data from Bloomberg.

EMPIRICAL RESULTS

Table 1 presents the summary statistics for key variables. Among the largest 100 publicly traded U.S. companies, the "Exposure to GAI" variable averages 0.35, with a median of 0.36 and a range spanning from 0.12 to 0.49.

Panel A displays the summary statistics for variables measured on November 30, 2022, which was the launch date of ChatGPT. The average number of employees stands at 136.8 thousand, while the median is 68.3 thousand. There is notable variability in the number of employees among companies, ranging from a minimum of 1.93 thousand to a maximum of 2300 thousand, with a 25th percentile value of 23.53 thousand and a 75th percentile value of 141.85 thousand.

TABLE 1. Summary Statistics

This table shows the summary statistics of key variables. There are 100 observations for all variables in this table.

Panel A: Summary Statistics of Variables Measured on 11/30/2022, the ChatGPT Launch Date							
Variable	Mean	Std. Dev.	Median	Min.	25 Percentile	75 Percentile	Max.
Exposure to GAI	0.35	*0.07*	0.36	0.12	0.31	0.39	0.49
Number of Employees	136.80	*284.01*	68.30	1.93	23.53	141.85	2300.00
Real Sales	18877	*26077*	8958	1560	5730	20421	153116
Real Operating Income	2871	*4398*	1729	−3939	935	3180	24943
Number of Employees/Assets	1.63	*2.39*	0.88	0.05	0.39	1.63	14.37
Real Sales per Employee	324.96	*532.30*	164.88	20.97	97.97	285.43	3078.03
Real Operating Income per Employee	92.45	*207.80*	35.86	−19.75	9.18	76.98	1315.23
Total Assets	109005	*125878*	67047	11106	40488	129928	902296
Number of Employees/Gross Fixed Assets	4.61	*4.08*	3.70	0.04	1.41	6.72	21.96
Number of Employees/Net Fixed Assets	9.71	*10.14*	7.83	0.07	2.75	13.43	57.31
Panel B: Summary Statistics of Variables Measured on 8/31/2023, 9 Months after ChatGPT Launch Date							
Variable	Mean	Std. Dev.	Median	Min.	25 Percentile	75 Percentile	Max.
Number of Employees	135.01	*264.03*	68.73	2.08	25.70	154.35	2100.00
Real Sales	19202	*27759*	9057	1756	5239	19474	161632
Real Operating Income	3207	*6166*	1669	−8958	971	3270	46173
Number of Employees/Assets	1.58	*2.30*	0.84	0.06	0.38	1.50	13.99
Real Sales per Employee	280.90	*390.05*	158.35	22.81	94.81	260.37	2187.38
Real Operating Income per Employee	65.96	*117.98*	32.42	−97.37	11.52	64.19	691.23
Total Assets	114151	*137216*	69157	13749	41352	133494	1041573
Number of Employees/Gross Fixed Assets	4.62	*4.49*	3.57	0.04	1.42	6.90	27.34
Number of Employees/Net Fixed Assets	9.87	*11.37*	7.91	0.07	3.04	13.18	63.73
Panel C: Summary Statistics of 9-Month Change Variables after the ChatGPT Launch during 11/30/2022–8/31/2023							
Variable	Mean	Std. Dev.	Median	Min.	25 Percentile	75 Percentile	Max.
Change in Number of Employees 9 M	−1.78	*22.61*	0.85	−200.00	0.00	3.00	28.57
Change in Real Sales 9 M	325	*7501*	176	−25928	−572	673	61969
Change in Real Operating Income 9 M	336	*5736*	12	−13122	−551	358	49646
Change in Number of Employees/Assets 9 M	−0.04	*0.16*	−0.01	−1.06	−0.06	0.01	0.29
Change in Real Sales per Employee 9 M	−44.06	*165.62*	−1.39	−966.56	−21.66	5.30	251.17
Change in Real Operating Income per Employee 9 M	−26.49	*110.36*	−0.48	−638.45	−12.71	2.32	232.79
Change in Total Assets 9 M	5146	*16934*	1714	−18010	−37	4577	139277
Change in Number of Employees/Gross Fixed Assets 9 M	0.01	*1.51*	−0.04	−2.92	−0.24	0.03	13.30
Change in Number of Employees/Net Fixed Assets 9 M	0.16	*3.30*	−0.13	−2.97	−0.59	0.06	30.56

As measures of the company's productivity, we use sales and operating income. Given the recent high levels of inflation, we have taken steps to mitigate concerns about inflation's impact on our productivity metrics. To address this, we have converted all sales and operating income figures into August 31, 2023, dollars using the U.S. Producer Price Index (PPI). These adjusted sales figures are referred to as *real sales*, and the converted operating income is termed *real operating income*.

As of November 30, 2022, the average latest quarterly real sales amount to $18.9 billion, while the standard deviation for quarterly real sales stands at $26.1 billion. Additionally, the average latest quarterly real operating income is $2.87 billion, accompanied by a standard deviation of $4.4 billion.

Considering that the firm's size may vary over time, we have adopted a scaling approach by dividing the number of employees by the total assets of the firm. The ratio of employees to total assets averages at 1.63 employees per one million dollars of total assets. The standard deviation for this ratio is 2.39, and the median value is 0.88.

As a labor productivity measure, we compute the real sales per employee by dividing the real sales figure by the number of employees. As depicted in Panel A, the quarterly real sales per employee averages at $324.96 thousand, accompanied by a standard deviation of $532.3 thousand. Likewise, the quarterly real operating income per employee stands at $92.45 thousand, with a standard deviation of $207.8 thousand. In terms of firm size, the total assets exhibit an average value of $109 billion, with a standard deviation of $126 billion.

As two alternative measures of employment, we adjust the number of employees relative to gross fixed assets and net fixed assets. As presented in the table, the ratio of employees to gross fixed assets amounts to 4.61 employees per million dollars of gross fixed assets, while the ratio of employees to net fixed assets is 9.71 employees per million dollars of net fixed assets.

Panel B shows the summary statistics of variables measured on August 31, 2023, the latest date of our sample, which is also 9 months after ChatGPT's launch date. The number of employees has an average of 135 thousand with a median of 68.73 thousand and a standard deviation of 264 thousand. As to the distribution, the minimum is 2.08 thousand, a 25th percentile of 25.7, a 75th percentile of 154.35 thousand, and a maximum of 2,100 thousand.

Compared to the distribution in Panel A, our results show that the minimum, 25th percentile, median, and 75th percentile values of the number of employees all increased slightly nine months after the launch of ChatGPT. However, the maximum number of employees decreased. These findings suggest that most companies did not reduce their number of employees. These findings are inconsistent with the conjecture laid out in Hypothesis 1, which we will examine more comprehensively in our subsequent analysis.

The average latest quarterly real sales for the sample of 100 companies stand at $19.2 billion, with a median of $9.06 billion as of August 31, 2023. Both figures are higher than their counterparts in Panel A, suggesting that companies have exhibited greater productivity nine months after the launch of ChatGPT. However, it's crucial to exercise caution in interpreting these numbers, as changes in sales can be influenced by various factors, including economic trends and firm size.

Regarding the average latest quarterly real operating income, it amounts to $3.21 billion, with a median of $1.67 billion. In comparison to Panel A, the average is higher while the median is lower. The ratio of employees to total assets averages at 1.58 employees per $1 million of total assets, with a median of 0.84. Both of these figures are lower than their counterparts in Panel A.

As indicated in Panel B, the quarterly real sales per employee averages at $280 thousand, with a median of $158 thousand. Similarly, the quarterly real operating income per employee stands at $65.96 thousand, with a median of

$32.42 thousand. All four of these figures are lower than their counterparts in Panel A. Once more, it's important to recognize that these changes could be attributed to various factors, including economic trends.

The total assets exhibit an average of $114 billion, with a median of $69 billion in Panel B. Both of these figures are higher than their counterparts in Panel A, indicating that company sizes are expanding. The ratio of employees to gross fixed assets is 4.62 employees per million dollars of gross fixed assets, while the ratio of employees to net fixed assets is 9.87 employees per million dollars of net fixed assets in Panel B. Both of these numbers are slightly higher than their counterparts in Panel A, indicating that companies have not reduced their employment levels.

In Panel C, we present the nine-month changes in these variables for each individual company. The average number of employees experienced a decrease of 1.78 thousand in the nine months following the launch of ChatGPT, with the median indicating an increase of 0.85 thousand. A closer look at the distribution reveals that approximately 25 percent of companies reduced their number of employees, while the remaining 75 percent actually increased their workforce.

As for real sales, there is an average increase of $325 million, with a median increase of $176 million. Real operating income shows an average increase of $336 million, with a median increase of $12 million. These figures indicate that the majority of companies did not decrease their employment and, at the same time, experienced an increase in their sales and operating income.

The number of employees scaled by total assets demonstrates a slightly negative average change of –0.04 employees per million dollars of total assets, with a median of –0.01. Real sales per employee, on the other hand, show an average decrease of –$44.06 thousand, with a median increase of $1.39 thousand. Similarly, real operating income per employee decreased by –$26.49 thousand per employee, with a median decrease of –$0.48 thousand per employee. In terms of total assets, there is an average increase of $5.1 billion, with a median increase of $1.7 billion.

In summary, our statistics reveal significant variability among different companies. On the employment front, there wasn't a substantial change in the number of employees over the nine-month period. While both sales and operating income increased during this period after the launch of ChatGPT, the average real sales per employee and real operating income per employee actually decreased. These findings suggest that companies did not experience uniform changes in their per-employee productivity. This heterogeneity is likely influenced by the varying levels of exposure to GAI among firms, as we expect GAI's impact on productivity to be more pronounced for those with higher exposure. Additionally, economic trends play a crucial role in understanding these variations.

To address these factors and better discern causal effects, we employ a difference-in-differences strategy that compares changes in firms with high AI exposure to those with low AI exposure before and after the launch of ChatGPT. In order to execute this difference-in-differences model and assess the varying impact of ChatGPT on different firms, we incorporate the nine-month change preceding the ChatGPT launch into our sample. Consequently, our sample for the regression analysis comprises 200 observations from 100 firms when the relevant variables are available.

TABLE 2. Pairwise Correlations

This table shows the pairwise correlations between variables. There are 200 observations for most variables except for Gross Profits, which has 192 observations. The two dates are ChatGPT launch date of November 30, 2022 and August 31, 2023. * shows significance at 5 percent level for this table.

Variable Name	Label	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Change in Number of Employees 9 M	(1)	1								
Change in Number of Employees/ Assets 9 M	(2)	0.4832*	1							
Change in Real Sales per Employee 9 M	(3)	−0.0477	−0.0648	1						
Change in Real Operating Income per Employee 9 M	(4)	−0.0259	−0.0008	0.8953*	1					
Exposure to GAI	(5)	0.1299	0.0352	−0.009	−0.0207	1				
Post GPT Indicator	(6)	−0.0842	−0.0792	−0.1921	−0.2056	0	1			
Exposure to GAI × Post GPT Indicator	(7)	−0.0382	−0.0386	−0.1593	−0.1777	0.1827	0.9661*	1		
Ln(Total Assets)	(8)	−0.1525	−0.0517	−0.0073	0.0078	0.0425	0.0271	0.0351	1	
Change in Number of Employees/ Gross Fix Assets 9 M	(9)	0.2076	0.4177*	−0.0496	−0.0105	0.091	0.0097	0.0485	−0.0224	1
Change in Number of Employees/Net Fix Assets 9 M	(10)	0.1741	0.3836*	−0.027	0.0106	0.1398	−0.0179	0.0298	−0.0123	0.9339*

Table 2 provides insight into the pairwise correlations between different variables. As evident in the table, various employment measures exhibit strong correlations with one another, as do different measures of per-employee productivity. The interaction term between exposure to GAI and the post-GPT indicator is correlated with its two constituent components. Apart from these anticipated high correlations, the remaining pairs of variables do not display significant correlations.

Table 3 presents the results of our regression analysis for the nine-month change in the number of employees, testing Hypothesis 1. In column 1, during the nine months following the launch of ChatGPT, the number of employees exhibits a positive association with GAI exposure, albeit not reaching statistical significance. In economic terms, the coefficient of 62.28 suggests that each 0.1 increase in GAI exposure is linked to an increase of six thousand employees. In column 2, we introduce the nine-month change prior to the ChatGPT launch as a benchmark. When incorporating the post-launch indicator and the interaction term, the coefficient on the interaction term is positive but remains statistically insignificant. This positive coefficient indicates that there wasn't a more substantial decrease in the number of employees in companies with higher GAI exposure. Moving to column 3, we include the control variable of firm size, represented by the natural log of total assets, along with sector fixed effects. The coefficient on the interaction term remains positive and statistically insignificant.

To address the outlier concern, we winsorize all continuous variables at both top and bottom 5 percent levels in columns 4 and 5. Indeed, the coefficients decrease in magnitude suggesting the influence of outliers to previous regressions. The coefficient on the interaction term is close to zero, suggesting that GAI doesn't have a differential impact on the number of employees across companies with varying levels of GAI exposure.

TABLE 3. Nine-Month Change in Number of Employees

This table shows the 9-month change in the number of employees after ChatGPT's launch date of November 30, 2022. Column 1 shows data for 100 firms during the 9 months after the launch. Columns 2 through 5 show data for 100 firms, including the 9 months before and after the launch. Columns 6 and 7 show data for 33 firms in the high GAI exposure tercile and 33 firms in the low GAI exposure tercile during the 9 months before and after the launch. Robust standard errors are in parentheses, where *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Dependent Variable = 9-Month Change in the Number of Employees						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GAI Exposure	62.28 (53.017)	6.23 (14.971)	−57.22** (28.927)				
Post Launch Indicator		−22.43 (21.202)	−22.47 (20.057)	−0.10 (3.456)	−0.51 (3.855)	−5.88 (7.053)	−5.72 (6.307)
Post Launch Indicator × GAI Exposure		56.04 (55.090)	56.63 (52.568)				
Winsorized GAI Exposure				5.87 (5.933)	−7.33 (8.264)		
Post Launch Indicator × Winsorized GAI Exposure				−0.53 (9.568)	0.68 (10.814)		
Tercile with High GAI Exposure						3.90 (2.478)	−5.11 (4.581)
Post Launch Indicator × High GAI Exposure Indicator						3.11 (7.237)	3.22 (6.764)
Ln(Total Assets)			−3.49* (2.085)		−0.23 (0.402)		−5.73* (3.264)
Constant	−23.46 (20.511)	−1.03 (5.368)		−0.86 (2.104)		−0.86 (2.107)	
Sector Fixed Effect	No	No	Yes	No	Yes	No	Yes
Observations	100	200	200	200	200	132	132
R-squared	0.033	0.035	0.211	0.007	0.114	0.029	0.228

To address the non-uniform distribution of GAI exposure, we incorporate the top tercile of firms (with high GAI exposure) and the bottom tercile of firms (with low GAI exposure) into our sample for columns 6 and 7. Instead of employing the continuous GAI exposure measure, we utilize the high GAI exposure indicator and its interaction term with the post-launch indicator. As demonstrated in columns 6 and 7, the coefficient on the interaction term remains statistically insignificant. Overall, the findings from Table 3 suggest that the launch of ChatGPT didn't have significant impact on the employment of top 100 companies, which is not consistent with the conjecture of Hypothesis 1.

Given the possibility of changes in firm size over time, we investigate the number of employees scaled by total assets in Table 4. In column 1, there is a positive association between GAI exposure and the nine-month change in employment per million dollars of total assets, although it is only marginally significant at the 10 percent level. However, when we utilize the benchmark of the nine-month change before the ChatGPT launch, as shown in the subsequent columns of this table, the coefficient on the interaction term remains statistically insignificant. These results align with our findings in Table 3, reinforcing the notion that the release of ChatGPT and subsequent events have not had a significant impact on employment.

Table 5 focuses on the change in labor productivity, measured by real sales per employee, nine months after the launch of ChatGPT, testing Hypothesis 2.

TABLE 4. Nine-Month Change in Number of Employees over Total Assets

This table shows the 9-month change in the number of employees scaled by total assets after ChatGPT's launch date of November 30, 2022. Column 1 shows data for 100 firms during the 9 months after the launch. Columns 2 through 5 show data for 100 firms, including the 9 months before and after the launch. Columns 6 and 7 show data for 33 firms in the high GAI exposure tercile and 33 firms in the low GAI exposure tercile during the 9 months before and after the launch. Robust standard errors are in parentheses, where *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variable = 9-Month Change in the Number of Employees Scaled by Total Assets							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GAI Exposure	0.61* (0.341)	–0.41 (0.707)	–0.88 (0.589)				
Post Launch Indicator		–0.39 (0.282)	–0.39 (0.248)	–0.01 (0.117)	0.02 (0.119)	–0.04 (0.062)	–0.04 (0.054)
Post Launch Indicator × GAI Exposure		1.02 (0.785)	1.02 (0.699)				
Winsorized GAI Exposure				0.38* (0.211)	0.01 (0.225)		
Post Launch Indicator × Winsorized GAI Exposure				–0.03 (0.331)	–0.12 (0.338)		
Tercile with High GAI Exposure						0.02 (0.067)	–0.03 (0.060)
Post Launch Indicator × High GAI Exposure Indicator						0.04 (0.082)	0.04 (0.075)
Ln(Total Assets)			–0.02 (0.015)		–0.00 (0.008)		–0.03 (0.021)
Constant	–0.26** (0.128)	0.13 (0.250)		–0.14* (0.076)		–0.04 (0.045)	
Sector Fixed Effect	No	No	Yes	No	Yes	No	Yes
Observations	100	200	200	200	200	132	132
R-squared	0.063	0.037	0.243	0.065	0.228	0.012	0.232

In column 1, there is a positive association between companies with higher GAI exposure and the change in real sales per employee. An additional 0.1 unit of exposure to ChatGPT corresponds to an increase of $32.9 thousand in quarterly sales per employee, which is marginally significant at the 10 percent level.

In column 2, when we incorporate both the nine-month changes before and after the ChatGPT launch, the interaction term becomes positive and significant at the 1 percent level. Interestingly, the coefficient for GAI Exposure is negative, suggesting that in the nine months before the ChatGPT launch, companies with more GAI exposure experienced a greater decrease in labor productivity. However, the coefficient on the interaction term is notably larger and positive, indicating that the launch of GAI significantly improved the labor productivity of companies with higher GAI exposure. The coefficient for the interaction term is 699.48, which completely overturns the coefficient of –370.42 on the GAI Exposure variable. As seen in the remaining columns of the table, the coefficient on the interaction term remains positive and statistically significant. These findings are consistent with the conjecture of Hypothesis 2.

In Table 6, we assess the change in labor productivity, specifically measured by real operating income per employee, in the nine months following the launch of ChatGPT. The signs of the coefficients align with those observed

TABLE 5. Nine-Month Change in Real Sales per Employee

This table shows the 9-month change in real sales per employee after ChatGPT's launch date of November 30, 2022. Column 1 shows data for 100 firms during the 9 months after the launch. Columns 2 through 5 show data for 100 firms, including the 9 months before and after the launch. Columns 6 and 7 show data for 33 firms in the high GAI exposure tercile and 33 firms in the low GAI exposure tercile during the 9 months before and after the launch. Robust standard errors are in parentheses, where *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Dependent Variable = 9-Month Change in Real Sales per Employee						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GAI Exposure	329.06* (196.192)	−370.42** (143.905)	−383.75* (215.598)				
Post Launch Indicator		−301.34*** (99.932)	−301.40*** (102.346)	−74.28** (34.920)	−81.00** (36.646)	−168.99*** (55.732)	−168.98*** (57.585)
Post Launch Indicator × GAI Exposure		699.48*** (243.310)	700.50*** (249.529)				
Ln(Total Assets)			−6.03 (12.250)		−3.22 (5.513)		−0.32 (16.020)
Winsorized GAI Exposure				−164.85** (69.801)	−166.40 (107.658)		
Post Launch Indicator × Winsorized GAI Exposure				177.49* (98.261)	197.62* (103.278)		
Tercile with High GAI Exposure						−97.20*** (34.564)	−105.00** (43.547)
Post Launch Indicator × High GAI Exposure Indicator						189.45*** (57.700)	189.45*** (59.649)
Constant	−158.61* (80.475)	142.73** (59.246)		54.85** (25.412)		68.98** (33.228)	
Sector Fixed Effect	No	No	Yes	No	Yes	No	Yes
Observations	100	200	200	200	200	132	132
R-squared	0.017	0.060	0.083	0.031	0.057	0.120	0.133

in Table 5. Notably, the coefficient on the interaction term between the post-launch indicator and GAI Exposure is positive and mostly significant, indicating that the introduction of GAI has a more favorable impact on enhancing the productivity of companies with higher levels of GAI exposure, consistent with our Hypothesis 2.

As a robustness check for employment, we also examine the nine-month change in the number of employees scaled by gross fixed assets, as illustrated in Table A1. Once again, the results do not indicate any adverse impact of GAI exposure on employment.

As a robustness check for labor productivity, we also investigate the nine-month change in real gross profit per employee, as presented in Table A2. The results are in alignment with the findings from sales and operating income per employee, reinforcing the consistency of our observations.

In summary, our findings indicate that the introduction of GAI tools has not had a negative impact on employment. Conversely, we observe positive and statistically significant effects of GAI exposure on labor productivity, as measured by sales per employee and operating income per employee. These results remain robust when accounting for firm size, sector fixed effects, and utilizing alternative employment and productivity measures.

TABLE 6. Nine-Month Change in Real Operating Income per Employee

This table shows the 9-month change in real operating income per employee after ChatGPT's launch date of November 30, 2022. Column 1 shows data for 100 firms during the 9 months after the launch. Columns 2 through 5 show data for 100 firms, including the 9 months before and after the launch. Columns 6 and 7 show data for 33 firms in the high GAI exposure tercile and 33 firms in the low GAI exposure tercile during the 9 months before and after the launch. Robust standard errors are in parentheses, where *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variable = 9-Month Change in Real Operating Income per Employee							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GAI Exposure	188.07 (134.813)	−256.22** (125.410)	−314.48** (156.162)				
Post Launch Indicator		−199.22*** (74.042)	−199.22*** (76.459)	−61.78** (30.580)	−63.62* (32.297)	−98.54*** (36.196)	−98.58*** (37.650)
Post Launch Indicator × GAI Exposure		444.30** (184.125)	444.35** (190.284)				
Winsorized GAI Exposure				−113.05* (64.550)	−150.78 (96.949)		
Post Launch Indicator × Winsorized GAI Exposure				127.87 (87.632)	133.56 (92.189)		
Tercile with High GAI Exposure						−60.15** (27.867)	−68.51** (27.729)
Post Launch Indicator × High GAI Exposure Indicator						104.43*** (38.663)	104.40** (40.174)
Ln(Total Assets)			−0.31 (6.622)		−2.00 (4.488)		1.65 (8.990)
Constant	−91.96* (53.529)	107.26** (51.154)		43.80* (22.668)		49.40* (26.305)	
Sector Fixed Effect	No	No	Yes	No	Yes	No	Yes
Observations	100	200	200	200	200	132	132
R-squared	0.013	0.061	0.072	0.044	0.080	0.094	0.099

CONCLUSION

This paper presents new evidence on the effects of generative AI on firm employment and productivity nine months after the launch of ChatGPT. Our findings indicate that exposure to generative AI, the most advanced and widely accessible AI technology to date, has not had any significant negative impact on employment. Instead, it had a positive effect on labor productivity. The advancement of science and technology, in the form of generative AI, proves to be beneficial to our society. These results contribute to our understanding of the intricate labor market implications of AI and offer guidance for shaping policies to maximize the benefits of these emerging technologies.

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Appendix

TABLE A1. Nine-Month Change in Number of Employees over Gross Fixed Assets

This table shows the 9-month change in the number of employees scaled by gross fixed assets after ChatGPT's launch date of November 30, 2022. Column 1 shows data for 100 firms during the 9 months after the launch. Columns 2 through 5 show data for 100 firms, including the 9 months before and after the launch. Columns 6 and 7 show data for 33 firms in the high GAI exposure tercile and 33 firms in the low GAI exposure tercile during the 9 months before and after the launch. Robust standard errors are in parentheses, where *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variable = 9-Month Change in the Number of Employees Scaled by Gross Fixed Assets							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GAI Exposure	3.67 (3.425)	−0.55 (1.200)	−2.10 (2.585)				
Post Launch Indicator		−1.45 (1.130)	−1.45 (1.076)	−0.59* (0.324)	−0.53 (0.329)	−0.10 (0.146)	−0.10 (0.133)
Post Launch Indicator × GAI Exposure		4.23 (3.629)	4.23 (3.446)				
Winsorized GAI Exposure				0.01 (0.646)	−1.31* (0.791)		
Post Launch Indicator × Winsorized GAI Exposure				1.31 (0.964)	1.14 (0.989)		
Tercile with High GAI Exposure						−0.00 (0.161)	−0.45 (0.286)
Post Launch Indicator × High GAI Exposure Indicator						0.29 (0.483)	0.29 (0.448)
Ln(Total Assets)			−0.01 (0.068)		0.00 (0.031)		−0.08 (0.078)
Constant	−1.27 (1.066)	0.18 (0.375)		0.01 (0.216)		−0.02 (0.042)	
Sector Fixed Effect	No	No	Yes	No	Yes	No	Yes
Observations	100	200	200	200	200	132	132
R-squared	0.026	0.024	0.121	0.064	0.163	0.006	0.212

TABLE A2. Nine-Month Change in Real Gross Profit per Employee

This table shows the 9-month change in real gross profit per employee after ChatGPT's launch date of November 30, 2022. Column 1 shows data for 96 firms during the 9 months after the launch. Columns 2 through 5 show data for 96 firms, including the 9 months before and after the launch. Columns 6 and 7 show data for 32 firms in the high GAI exposure tercile and 30 firms in the low GAI exposure tercile during the 9 months before and after the launch. Robust standard errors are in parentheses, where *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent Variable = 9-Month Change in Real Gross Profit per Employee							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GAI Exposure	206.92 (128.933)	−255.38** (116.045)	−274.57** (136.675)				
Post Launch Indicator		−189.83*** (69.941)	−189.84*** (72.273)	−64.40** (30.109)	−71.40** (31.236)	−88.61** (35.539)	−88.59** (36.858)
Post Launch Indicator × GAI Exposure		462.29*** (173.465)	462.52** (179.564)				
Winsorized GAI Exposure				−112.32** (55.446)	−116.62 (76.050)		
Post Launch Indicator × Winsorized GAI Exposure				163.69* (83.728)	184.48** (86.639)		
Tercile with High GAI Exposure						−58.04** (26.484)	−63.28** (25.051)
Post Launch Indicator × High GAI Exposure Indicator						104.99*** (37.661)	105.00*** (39.084)
Ln(Total Assets)			−1.39 (6.072)		−2.48 (4.063)		−0.70 (8.267)
Constant	−93.09* (51.381)	96.74** (47.451)		35.73* (19.619)		39.82 (25.203)	
Sector Fixed Effect	No	No	Yes	No	Yes	No	Yes
Observations	96	192	192	192	192	124	124
R-squared	0.019	0.048	0.062	0.024	0.061	0.089	0.094

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