

Operational leanness and retail firm performance since 1980

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ABSTRACT

Lean is one of the most pervasive and powerful paradigms in Operations and Supply Chain Management. As a theory, lean has been well tested in manufacturing. Lean in retail has received less attention. There is good reason to think that seminal constructs from lean, such as inventory slack reduction and capacity slack reduction, may explain a great deal of the variance in retail firm performance. Therefore this paper tests lean-based propositions pertaining to the relationships between inventory slack, capacity slack, market instability and firm market performance. Using retail firm data from a 35 year period, we find that lean thinking in its basic unadorned form helps explain retail performance remarkably well. From both a snapshot and quarterly difference perspective and regardless of whether we look at capacity slack or inventory slack, lean produces superior, lasting returns for retailers.

1. Introduction

Lean is one of the most prominent ideas in Operations and Supply Chain Management (OM/SCM) in terms of uptake among practitioner organizations (particularly manufacturers), as well as in terms of lean's diffusion in the academic literature and across the business school curriculum. The performance effects of lean on manufacturing have been studied with surveys (e.g. [Inman and Mehra, 1993](#); [Droge and Germain, 1998](#); [Shah and Ward, 2003](#)) and with secondary data (e.g. [Irvine, 2003](#); [Capkun et al., 2009](#); [Cannon et al., 2008](#); [Eroglu and Hofer, 2011](#); [Koumanakos, 2008](#); [Swamidass, 2007](#)). The literature generally supports the fundamental notion that leaner inventories and capital stocks are associated with better performance, although this is not a universal finding; and moreover, with respect to inventories especially, the relationship with performance may be non-linear ([Eroglu and Hofer, 2011](#); [Isaksson and Seifert, 2014](#); [Kesavan and Mani, 2013](#)).

Lean thinking has also migrated into service operations ([Dobrzykowski et al., 2016](#); [Gupta et al., 2016](#); [Lee et al., 2008](#); [Malmbrandt and Åhlström, 2013](#)), including retail operations ([Carmignani and Zammori, 2015](#); [Cox and Chicksand, 2005](#)). The impact of lean initiatives in retail is worthy of inquiry as this industry is the third largest non-government sector in terms of employment in the United States. Retail accounts for 10% of employment in the United States versus 8% in manufacturing ([Figeroa and Woods, 2007](#)). Similarly, in the European Union, retail is the third largest sector, accounting for 8% of the total employment,

versus 15% in Manufacturing and 10% in Health and Social Services sectors ([Reynolds and Cuthbertson, 2014](#)). The economic significance of retail means that it is important for OM/SCM scholars to understand how prescriptions from our field play out in the retail context. Perhaps more importantly from a theory perspective, there are important differences between retail and manufacturing. Therefore studying lean in retail can help us understand some of the boundary conditions of lean as a theory.

Lean is certainly one of the most formidable paradigms in OM/SCM. However, thought leaders in the field should be judicious when it comes to predicting and prescribing to one area, such as retail, based on theory developed in other areas (primarily manufacturing in this case). Indeed several theories and empirical findings from the literature suggest that retail may be outside of the boundary conditions within which we should expect lean theory to hold. Two bedrock tenets of lean improvements are reductions in inventory slack, which measures inventory in excess of what is anticipated to meet demand, and capacity slack, which measures sales generated per dollar of plant, property, and equipment ([Hendricks et al., 2009](#); [Isaksson and Seifert, 2014](#); [Kesavan and Mani, 2013](#); [Kovach et al., 2015](#); [Modi and Mishra, 2011](#)). In manufacturing, reductions in inventory contribute to profitability by reducing costs, such as those related to storage, material tracking, obsolescence, pilferage and the like. Inventory reductions also have positive indirect effects on profitability (e.g. effects associated with increased quality). Certainly many of these same direct and indirect effects accrue in the retail sector.

However, when it comes to retail, there are other sides to the

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inventory and capacity story. [Chen et al. \(2007\)](#) find that lower inventory is associated with superior long term stock market returns across all sectors, but the effect is not as strong for retailers as it is for manufacturers ([Chen et al., 2005](#)). A key benefit of excess inventory and capacity in manufacturing is that it can act as a buffer against instability ([Hendricks et al., 2009](#)). This is true in retail as well; however, other factors may make retail different: In particular, retail inventory volume itself can drive demand because it may result in fewer stockouts, fuller appearing shelves, and larger product facings ([Ton and Raman, 2010](#)).

The efficient use of capacity is another key aspect of lean. Here again, there are some possible departures between the dominant theories of lean in manufacturing versus retail. In other words, lean suggests that leaner firms are able to satisfy demand more efficiently with less physical capacity (i.e., property, plant and equipment) which will lead to improved financial performance. However, [Shockley et al. \(2015\)](#) suggest that the capacity-performance relationship may depend on other factors, such as product gross margins and the degree to which a change in physical capital investment is accompanied with a complimentary change in human resources investment—for example reductions in store personnel balanced with increases in retail process automation. Therefore, performance improvement is not so much a function of reducing physical capital, but instead it is a matter of choosing between a number of equally effective combinations of resources.

In light of the foregoing observations, the objective of this study is to empirically examine the relationship between leanness and firm performance in the retail industry. We first examine the association between the levels of operational slack within retail firms and performance over the 35 year period from 1980 through 2014. When conducting this assessment, we examine slack in two ways: First, we examine snapshots of the levels of operational slack within firms, to determine if a firm's level of leanness relative to other firms is related to performance differences. We also build on prior research and explore if the relationships between levels of slack and performance are linear in nature or if they are better described with more complex non-linear models. Finally, we examine whether the nature of these relationships differ when demand is unstable.

In addition to the analysis just described, we examine whether quarterly differences in a particular firm's slack levels correspond to changes in that firm's performance in later periods. This approach was selected to address concerns which suggest that longitudinal studies provide richer inferences for economic relationships when they are

examined from a dynamic viewpoint ([Hsiao, 2007](#); [Nerlove, 2005](#)). Finally, for the quarterly difference relationships which are determined to be of significance, we employ Granger causality tests to assess the possibility that causal relationships might exist.

In the next section, we discuss the relevant literature and develop our hypotheses. We then discuss the data, measures and empirical methodology. Finally, we discuss our findings, their contribution to the existing body of knowledge, their managerial implications, and the limitations of our study.

2. Literature review and hypotheses

Lean management has been widely linked to improved operational and firm performance for manufacturers ([Chavez et al., 2013](#); [Eroglu and Hofer, 2011](#)). Firms adopting lean management philosophies focus on eliminating waste and improving processes ([Womack et al., 1990](#)). Waste may take many forms including, product defects, excess inventory, overproduction, excess movement, inefficient transportation, excessive waiting times, and overprocessing ([Hines and Rich, 1997](#)). Reductions in these areas of waste improve the efficiency with which a firm utilizes its resources ([Spear and Bowen, 1999](#)). Such improvements, which result in superior resource efficiency for a firm, have been shown to lower costs and, ultimately, improve shareholder value ([Holweg, 2007](#); [Modi and Mishra, 2011](#)).

In a retail context, lean implementation can typically be categorized as efforts which focus on waste reduction to lower costs, increase sales margins, improve resource efficiency and hence improve profitability ([Lind, 2005](#)). For managers, specific waste reduction actions may include the improvement of inventory management policies, the closing of unprofitable store locations, optimizing the use of retail space within stores to focus on more profitable products, better utilization of employee talent, improvements in transportation and logistics efficiency, and preventing defective merchandise from reaching stores ([Jaca et al., 2012](#)).

As stated above, we adopt two measures of operational slack widely used in prior studies to conduct this study: inventory slack and capacity slack.

2.1. Inventory slack

Inventory affects performance through many paths including cash flow, the costs of capital to buy and hold inventory, as well as

Table 1
Summary of Measures and Calculations.

Measure	Description	Calculation	Sample Mean
Unexplained Stock Return (USR)	Measured as the difference between the actual and predicted quarterly stock return.	Actual Quarterly Stock return – Predicted Stock Return (estimated using the Fama French Model.)	0%
Firm Size (SIZE)	Total Assets is used as a proxy for firm size.	Total Assets is used as a proxy for firm size. Due to linearity issues, the natural log of Total Assets is utilized in the analyses.	\$1503 million
Leverage (LEV)	Ratio of debt to total firm assets.	(Total Long-term Debt ÷ Total Assets).	0.22
Recession (RECESS)	A binary indicator variable denoting the presence of an economic recession.	A value of 1 represents a quarter in which the U.S. economy experienced an economic recession.	N/A
Instability (INST)	The overall volatility of demand.	Range of the ARIMA X-12 seasonal indices calculated using the prior 20 quarters of sales.	0.43
Gross Margin (GM)	The ratio of the profit divided by sales.	(Sales – Cost of Goods Sold)/Sales	0.21
Days of Sales Outstanding (DSO)	The average number of days required to collect revenue after a sale is made.	(Accounts Receivables ÷ Sales) x 91 days.	18.7 days (Avg. Quarterly $\Delta = -0.12$ days)
Days of Payables Outstanding (DPO)	The average number of days a company takes to pay creditors.	(Accounts Payable ÷ Purchases) x 91 days where Purchases = (Cost of Goods Sold + Change in Inventory).	41.0 days (Avg. Quarterly $\Delta = +0.20$ days)
Inventory Slack (INVSLACK)	The average number of days that inventory is held before it is sold.	(Inventory ÷ Cost of Goods Sold) x 91 days.	75.1 days (Avg. Quarterly $\Delta = -0.11$ days)
Capacity Slack (CAPSLACK)	The ratio of Plant, Property, and Equipment (Net) to Sales indicates the sales generated per dollar of PPE.	Plant, Property, and Equipment (Net)/Sales. Due to linearity issues, the natural log of the measure is utilized in the analyses.	0.94 (Avg. Quarterly $\Delta = -0.04$)

Table 2
Sample descriptive statistics (uncentered and unstandardized) by Two-Digit SIC Code.

2-digit SIC Code	Industry Title	# of Firms in Sample	# of Observ.	USR Mean (SD)	SIZE Mean (SD)	LEV Mean (SD)	INST Mean (SD)	GM Mean (SD)	DSO Mean (SD)	DPO Mean (SD)	INVSLACK Mean (SD)	CAPSLACK Mean (SD)
52	Building Materials, Hardware, Garden Supply and Mobile Home Dealers	49	1635	0.00 (0.96)	2871.34 (8781.5)	0.22 (0.17)	0.45 (0.03)	0.28 (0.16)	18.86 (19.97)	44.49 (24.72)	98.72 (42.29)	0.78 (0.56)
53	General Merchandise Stores	124	4710	0.00 (0.98)	5358.43 (18315.05)	0.21 (0.15)	0.3 (0.05)	0.21(3.88)	20.05 (29.47)	45.17 (22.34)	111.3 (52.06)	0.76 (0.64)
54	Food Stores	136	4830	0.00 (0.97)	2481.45 (4960.7)	0.26 (0.19)	0.42 (0.14)	0.12 (6.21)	10.03 (16.2)	28.59 (16.38)	36.62 (22.61)	0.84 (3.93)
55	Automotive Dealers and Gasoline Service Stations	72	2368	0.00 (0.95)	1323.11 (2144.58)	0.21 (0.16)	1.66 (0.04)	0.22 (0.72)	23.99 (32.52)	39.83 (45.93)	97.87 (80.23)	0.77 (1.4)
56	Apparel and Accessory Stores	142	5615	0.00 (0.98)	711.86 (1411.14)	0.11 (0.14)	0.32 (0.04)	0.36 (0.13)	10.88 (18.84)	42.61 (21.05)	105.19 (51.63)	0.62 (0.29)
57	Home Furniture, Furnishings and Equipment Stores	110	3365	0.00 (0.97)	742.89 (1937.7)	0.14 (0.14)	0.51 (0.04)	0.21 (4.2)	22.56 (36.52)	50.53 (28.68)	116.4 (58.38)	0.56 (0.63)
58	Eating and Drinking Places	322	9974	0.00 (0.99)	597.55 (2564.74)	0.25 (0.3)	0.42 (0.06)	0.18 (1.03)	10.31 (15.47)	25.61 (25.89)	12.42 (20.52)	1.8 (1.93)
59	Miscellaneous Retail	400	10,995	0.00 (0.97)	1086.61 (4473.33)	0.18 (0.26)	0.24 (0.07)	0.22 (6.16)	30 (34.58)	50.94 (34.32)	99.71 (81.21)	0.61 (2.64)
Total		1355	43,492									

obsolescence costs (Demeter and Matyusz, 2011). Inventory reduction mediates the relationship between lean practice implementation and financial performance (Hofer et al., 2012). Two pathways by which inventory affects firm performance are through inventory's effects on quality and on lead time (Hopp and Spearman, 2004). Inventory can buffer the impact of quality problems and other operational problems, which is often explained via the metaphor of the boat on the rocky river in which lowering inventory (water) forces the organization to confront problems (rocks that had been obscured by water). Moreover, inventory increases cycle times, which can make firms less responsive. These bedrock ideas of the OM field are well explicated in operations classics such as Hall (1983) and Womack et al. (1990). These principles may apply more to work in process, which is critical to manufacturers, as opposed to finished goods, which are the most critical inventory for retailers. However, the inventory to operational performance causal link is likely strong in retail environments. When inventory turnover is low, products spend more time on the shelves. This increases the window of exposure for damage, pilferage and spoilage/expiration. Moreover, excessive inventories increase the likelihood that items will be lost or misplaced. When this results in stockouts, a current sale is lost, and more importantly, customers are less likely to return (Ton and Raman, 2010). Finally, higher inventory supply chains tend to have longer order cycles thus making them less responsive to changing tastes and preferences, which is particularly detrimental in segments such as apparel and home furnishings (Martinez et al., 2015).

Looking across retail firms, Chen et al. (2007) find evidence that firms with lower inventory have better performance when it comes to longer term stock market performance (but not when it comes to cross sectional differences across firms at a point in time). Shockley et al. (2015) find a positive association between inventory turnover and sector adjusted return on assets and return on sales. Several underlying mechanisms explain the observed link between lower inventory slack and improved firm performance – a lower inventory slack level implies that a firm will have lower holding costs, reduced write-off expenses, and a faster cash-cycle (Hendricks and Singhal, 2009) – all of which improve the cash flow cycle time – which corresponds to a faster rate of return on investments (ROI) and ultimately improved shareholder value (Gunasekaran et al., 2004).

These conceptual arguments and empirical findings form the basis for our first hypothesis:

H1a. Retail firms with lower levels of inventory slack will exhibit

higher levels of firm market performance.

On the other hand, some literature suggests that in retail, higher inventories (and lower inventory turnovers) could increase performance or be neutral with respect to performance. Classic inventory theory treats demand as a given. By contrast, in retail, inventory can generate demand. First, higher inventories can drive demand in and of themselves. For example, customers are more likely to buy when shelves appear full (Baron et al., 2011; Larson and DeMarais, 1990). Higher inventories also decrease the likelihood of stock-outs; and customers shop more at stores with fewer stock-outs (Dana and Petruzzzi, 2001). Second, product variety (i.e. the number of substitute products available to fill a given consumer need) increases individual store demand (Borle et al., 2005); and variety and inventory tend to be positively associated (Rajagopalan, 2013). Moreover, firm level retailer inventory predicts (positively) future sales (Kesavan et al., 2010). To the extent that inventory enhances demand in these ways, we would expect decreases in inventory levels to be associated with decreases in firm sales revenue, which would decrease returns, and hence, negatively impact shareholder value.

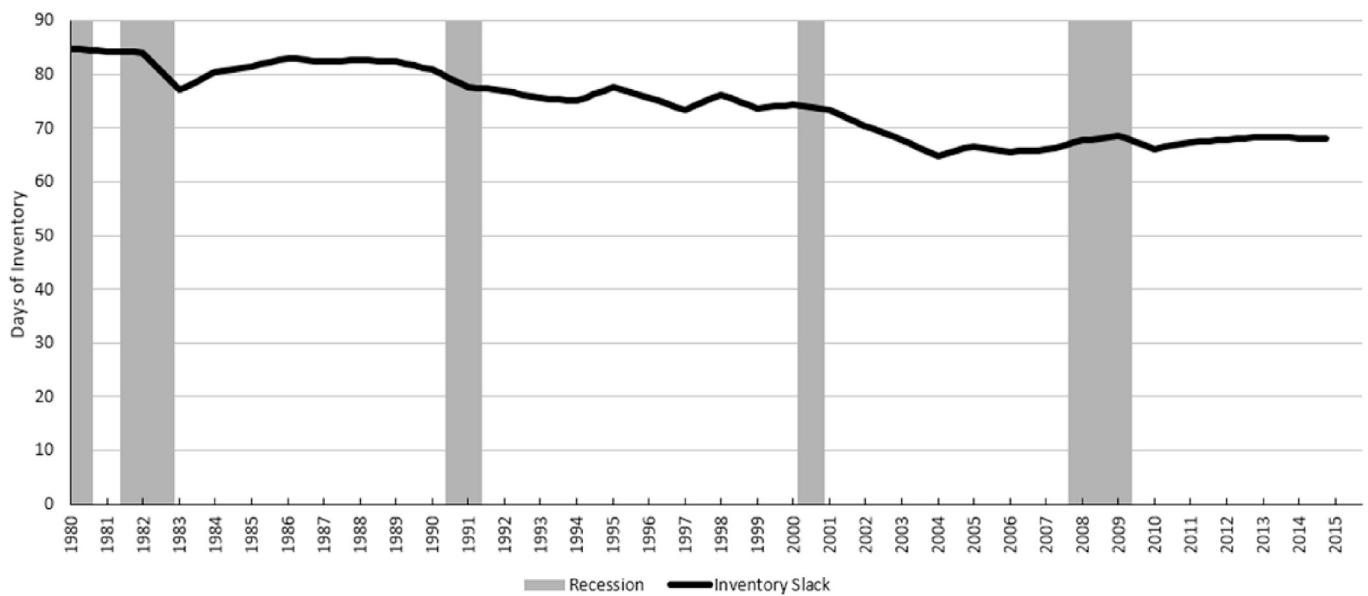
The above logic and empirical results are the basis for our second hypothesis, which is a counter-hypothesis to H1a.

H1a (Alternate). Retail firms with lower levels of inventory slack will exhibit lower levels of firm stock market performance.

2.2. Capacity slack

Recent econometric studies of manufacturers have found that capacity slack is negatively associated with firm performance overall (Kovach et al., 2015; Modi and Mishra, 2011). Lower capacity slack, achieved through lean initiatives typically results in waste reductions (Holweg, 2007). Specifically, a lower level of capacity slack implies that a firm is utilizing its resources more efficiently which may lead to lower costs, increased margins, and ultimately higher profits (Harry and Schroeder, 2005). For a retail firm, having less capacity slack means that the firm is generating sales more efficiently from its resources, hence a leaner firm will generate more sales relative to the value of its stores, real estate, equipment, and other assets owned by the firm. These savings, resulting from superior resource efficiency, will improve a firm's return on assets, which has been widely linked to improved shareholder value (Hendricks and Singhal, 2005). Based on the foregoing reasoning and prior empirical findings, we hypothesize:

(a) Inventory Slack



(b) Capacity Slack

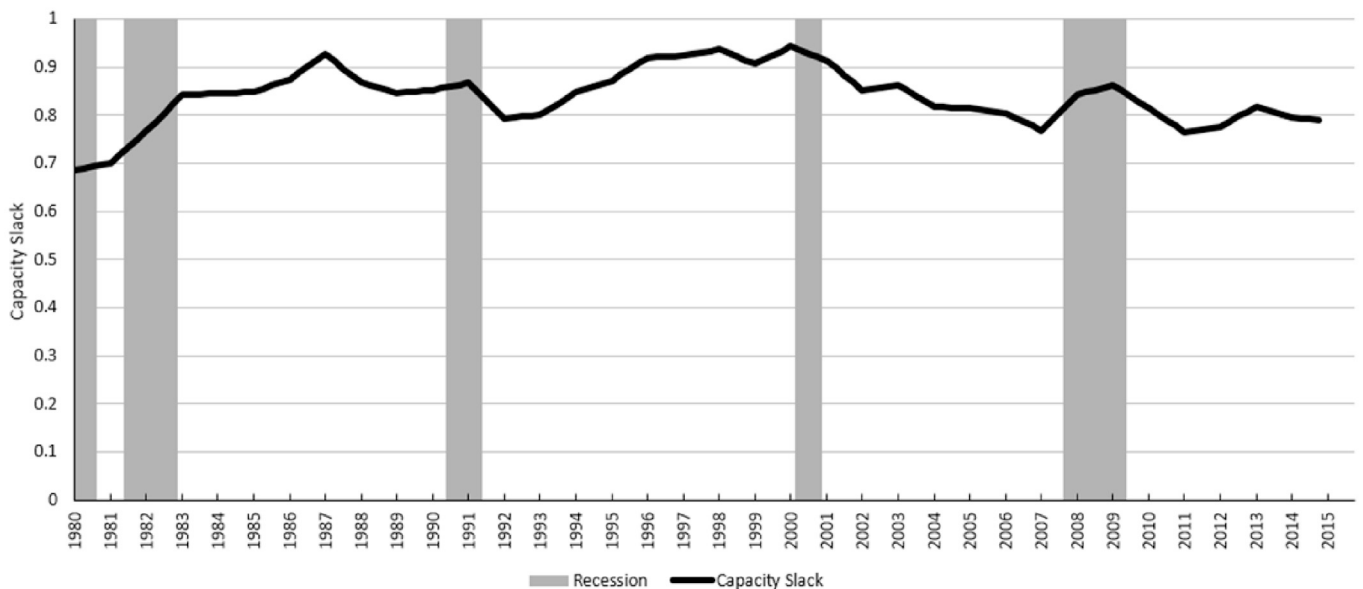


Fig. 1. Retailer Operational Slack Levels (1980–2014).

H1b. Lower capacity slack is related to higher retail firm stock market performance.

Though the literature generally supports the above hypothesis, a counter argument can be made that this relationship may not hold true in the retail arena. Equifinality is the notion that different mixes of resources assembled appropriately can produce similar levels of performance (Doty et al., 1993; Gresov and Drazin, 1997; Isaksson and Woodside, 2016; Kulins et al., 2016). Marlin and Geiger (2015) show that equifinality exists in their study of the relationship between various types of organizational slack and innovation. Likewise, service operations resource complimentary theory suggests two directions that can be

equally profitable: (1) Utilizing larger inventories typically with higher gross margins and (2) higher capital intensity (achieved through more store locations, better located stores, superior information technology, etc.) in conjunction with lower inventory (typically with lower gross margins) (Shockley et al., 2015). Similarly, the amount of shelf space in stores, which is a revenue generating asset (Wang et al., 2015), may decrease when capacity slack is reduced; however, the revenue generated may not decrease if the shelf space is managed more efficiently. In line with this, Gaur et al. (2005) show that the same level of performance can be achieved by varying the combination of capital intensity and inventory—substituting one for the other. This is reinforced in trade press

Table 3
Operational Slack and Unexplained Stock Returns (USR_{it}).

	Control Variables	Model 1: Slack Factors over Sample Period	Model 2: Non-Linear Slack Factors	Model 3: Slack and Instability Interactions
SIZE _{it}	−0.0967*** (0.00751)	−0.0816*** (0.00777)	−0.0797*** (0.00783)	−0.0834*** (0.00780)
LEV _{it}	−0.000247 (0.0344)	0.0336 (0.0347)	0.0284 (0.0347)	0.0313 (0.0347)
RECESS _t	−0.00675 (0.0139)	−0.00292 (0.0140)	−0.00257 (0.0140)	−0.00311 (0.0140)
INST _t	−0.417*** (0.112)	−0.310** (0.113)	−0.296** (0.113)	−0.334** (0.119)
GM _{it}	−0.00108 (0.00137)	−0.00189 (0.00138)	−0.00244 (0.00141)	−0.00194 (0.00138)
DSO _{it}	−0.000985** (0.000338)	−0.000485 (0.000353)	−0.000478 (0.000353)	−0.000468 (0.000353)
DPO _{it}	−0.000136 (0.000271)	0.000469 (0.000282)	0.000524 (0.000283)	0.000431 (0.000283)
INVSLACK _{it} [H1a]		−0.00114*** (0.000188)	−0.00191*** (0.000459)	−0.00155*** (0.000278)
CAPSLACK _{it} [H1b]		−0.0991*** (0.0124)	−0.117*** (0.0154)	−0.130*** (0.0180)
(INVSLACK _{it}) ²			0.000002 (1.29e-06)	
(CAPSLACK _{it}) ²			−0.0106* (0.00496)	
INVSLACK _{it} x INST _t [H2a]				0.000961* (0.000471)
CAPSLACK _{it} x INST _t [H2b]				0.0736* (0.0297)
Intercept	0.721*** (0.0763)	0.595*** (0.0814)	0.614*** (0.0834)	0.616*** (0.0835)
Observations	43,925	43,492	43,492	43,492
Number of Firms	1359	1355	1355	1355
F-Statistic	26.33***	35.93***	30.10***	30.66***

Standard errors in parentheses.

*** p < .001, ** p < .01, * p < .05.

Note: Values related to hypotheses tests are denoted in **bold italic** font.

accounts of retailers reducing inventory and human “touches” and thus costs by transitioning from standard equipment, bought based on lowest cost, toward more elaborate or customized equipment (Lind, 2005). Thus, if retailers can achieve the same performance level, by various combinations of capital, labor and inventory, then differences in capacity slack might not be systematically associated with performance.

2.3. Market instability

Market instability, exhibited through demand volatility, is a fundamental challenge for retail firms (Stratton and Warburton, 2003). Less lean firms (i.e. those with higher levels of operational slack) may be better positioned to withstand unstable demand environments (Hendricks et al., 2009; Kovach et al., 2015; Lee, 2004; Kleindorfer and Saad, 2005). Demand instability makes it more difficult to accurately predict demand in advance. Therefore to avoid stockouts (or maintain any particular service level), retailers need to carry a higher level of safety stock when demand is unstable (Chopra and Sodhi, 2004; Craighead et al., 2007; Tang, 2006). Similarly, maintaining extra capacity can provide retailers the volume flexibility to respond to unanticipated demand (Manikas and Patel, 2016). *Ceteris Paribus*, generous safety stock and safety capacity policies increases inventory and capacity. However, oftentimes the cost of maintaining the higher inventories and capacities is less than the costs that would be incurred from being unable to meet demand when it occurs (i.e. lost margin from stockouts and the associated declines in customer satisfaction, declines in repeat traffic and so on.) This logic suggests that when demand uncertainty increases, retailers who maintain or increase inventory and/or capacity might suffer less in terms of operational performance than retailers who do not respond or who respond with inventory and capacity reductions. We

expect these changes in operational performance to be reflected in retailers' financial performance. Therefore, in contrast to our primary hypotheses which advocate that lower slack levels relate to improved stock market performance, the flexibility resulting from higher levels of slack allows firms to better react during times of high market instability, and consequently outperform leaner firms. These arguments lead to our second set of hypotheses:

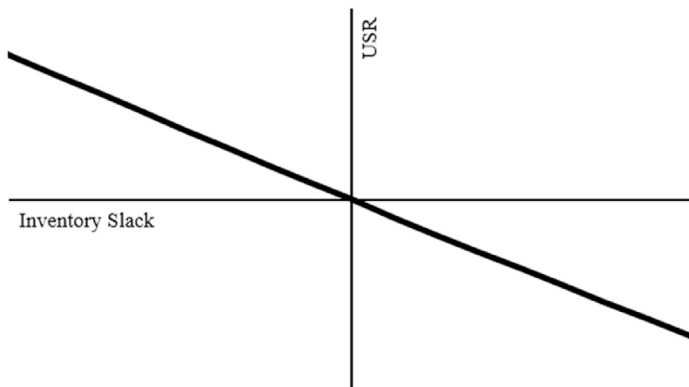
H2a. Market instability moderates the relationship between lower inventory slack and higher firm market performance, such that higher instability reduces the relationship between lower inventory slack and higher firm stock market performance.

H2b. Market instability moderates the relationship between lower capacity slack and higher firm market performance, such that higher instability reduces the relationship between lower capacity slack and higher firm stock market performance.

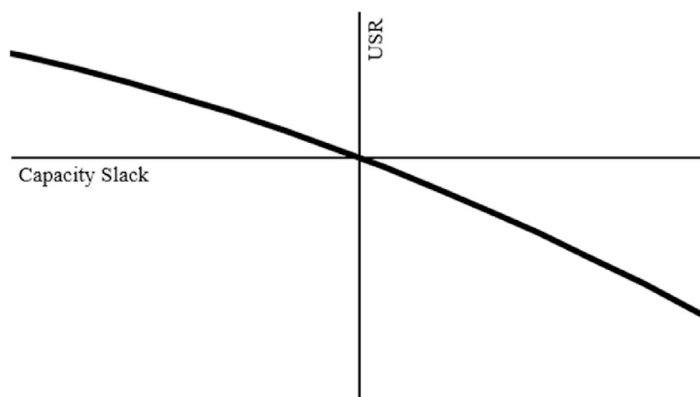
2.4. Changes in inventory and capacity slack

Our first two hypotheses are consistent with prior studies, which mostly use fixed, cross sectional measures of slack and performance. By contrast, most managers are interested in understanding what levers to manipulate *within* their organizations in order to increase their firms' performance. It is important for researchers to address this question with as much precision as possible. While cross-sectional research designs partially address this question, the best answer comes from a first-difference analysis. A first-difference analysis examines whether within company changes in the variables of interest — i.e. inventory slack and capacity slack in the present — affect performance at a later time. This may be especially important in the present domain since lean has a mixed

(a) Inventory Slack Level and Unexplained Stock Returns (USR)



(b) Capacity Slack Level and Unexplained Stock Returns (USR)

**Fig. 2.** Operational Slack and Firm Performance (99th Percentile of Slack Levels [$\pm 2.58 \sigma$]).

record as far as the success of implementations producing positive business results; and additionally it is not always clear which elements of lean (e.g. JIT, TQM) improve performance.

As discussed in the support for the first hypothesis, it is generally believed that leaner firms will experience higher levels of performance. Building on this premise, it can be expected that reductions in inventory slack will correspond to improvements in cash flow and reductions in capacity slack will correspond to improvements in returns on assets, both of which will improve shareholder value. In line with this, we predict:

H3a. Reductions in inventory slack will be positively associated with improvements in retail firm stock market performance.

H3b. Reductions in capacity slack will be positively associated with improvements in retail firm stock market performance.

Finally, as discussed in the support for the second hypothesis, it is generally believed that market instability moderates the relationship between operational slack and performance. The following hypothesis tests this idea from a longitudinal perspective (parallel to Hypotheses 2a and 2b) rather than a cross sectional one. Explicitly, we predict:

H4a. Market instability moderates the relationship between changes in inventory slack and changes retail firm market performance, such that higher instability reduces the relationship between inventory slack reductions and stock market performance improvements.

H4b. Market instability moderates the relationship between changes in capacity slack and changes retail firm market performance, such that higher instability reduces the relationship between capacity slack reductions and stock market performance improvements.

3. Methodology

3.1. Data sample

We collected firm-level quarterly financial data published in the COMPUSTAT database for retailers publicly traded on the U.S. stock exchanges between 1980 and 2014 (Standard and Poor's, 2016). Firms may occasionally take up to six months to report their financial performance data, which led to the selection of December 31, 2014 as the end point of the sample as it represents the final complete year of data available at the initiation of this study. Retail firms were identified as those with two-digit Standard Industrial Classification (SIC) codes ranging from 52 to 59. The quarterly firm data was associated with the calendar date in which it was reported, rather than with the fiscal quarter, due to the variability in fiscal reporting dates across firms.

A subtle difference in this study's dataset compared with many prior studies is the examination of firms at the quarterly level versus the annual level. As this study's focus is on the firm performance implications of operational slack, it is believed that, compared to annual data, quarterly data will more accurately reflect the reactions of an efficient market to changes in a firm's slack (Fama, 1998).

The dataset includes entries for retail firms that reported quarterly data during the 35 year period of study. As the number firms reporting data varies quarter to quarter, this process resulted in an unbalanced panel dataset. To avoid presenting results influenced by outliers, after calculating the variables of interest, we winsorize our sample at the 1% and 99% levels (Hendricks and Singhal, 2005). This results in a final sample containing 43,492 observations across 1355 firms which equates to an average of approximately eight years of data per firm. Summary

Table 4
Quarterly Difference in Operational Slack and Unexplained Stock Returns (ΔUSR_{it}).

	Control Variables	Model 4: Slack Factors	Model 5: Slack and Instability Interactions
SIZE_{it}	−0.00793 (0.0115)	−0.0101 (0.0116)	−0.0100 (0.0116)
LEV_{it}	0.0283 (0.0537)	0.0380 (0.0566)	0.0378 (0.0566)
RECESS_t	−0.0229 (0.0209)	−0.0232 (0.0211)	−0.0232 (0.0211)
INST_t	−0.0615 (0.166)	−0.0710 (0.168)	−0.0712 (0.168)
GM_{it}	0.00961 (0.00695)	−0.0866** (0.0283)	−0.0865** (0.0283)
ΔDSO_{it}	−0.00233** (0.000737)	0.000563 (0.000920)	0.000661 (0.000921)
ΔDPO_{it}	0.00136** (0.000411)	0.00140** (0.000441)	0.00132** (0.000442)
$\Delta\text{INVSLACK}_{it}$		−0.000776* (0.000362)	−0.00161** (0.000568)
[H3a]			
$\Delta\text{CAPSLACK}_{it}$		−0.197*** (0.0410)	−0.167* (0.0674)
[H3b]			
$\Delta\text{INVSLACK}_{it} \times \text{INST}_t$ [H4a]			0.00199 (0.00105)
$\Delta\text{CAPSLACK}_{it} \times \text{INST}_t$ [H4b]			−0.0700 (0.133)
Intercept	0.0566 (0.114)	0.0991 (0.117)	0.0988 (0.117)
Observations	41,318	40,373	40,373
Number of Firms	1310	1297	1297
F-Statistic	3.177***	11.35***	9.724***

Standard errors in parentheses.

*** $p < .001$, ** $p < .01$, * $p < .05$.

Note: Values related to hypotheses tests are denoted in **bold italic** font.

statistics for the variables used in our analyses are included with the variable descriptions presented in Table 1. The sample size utilized in the quarterly difference analysis is slightly reduced (to 40,373 observations across 1297 firms) as consecutive quarters of complete data are required for each observation.

Descriptive statistics segmented by two-digit SIC code, which are presented in Table 2, show that the industries with the highest levels of inventory slack (SIC 57 and 53) represent firms with retail stores that typically have on-hand inventories of durable goods. In contrast, the industries with the lowest inventory slack (SIC 58 and 54) consist of firms that sell food and beverage items, which are often perishable. These same two food related industry groups have the highest levels of capacity slack, which might be due to the limited ability of food and beverage firms to sell their products outside of physical retail locations; whereas, the industries with the lowest capacity slack (SIC 57 and 59) both include firms that have the capability to sell products through catalog and online channels (for example, SIC 59 includes online retailers such as Amazon.com).

3.2. Independent variables

Building on prior studies, we utilize existing operational slack metrics to measure the levels of slack within firms. First, in line with Kovach et al. (2015), we utilize inventory slack as our initial measure of retail firm slack:

Inventory Slack - (INVSLACK_{it}): is defined as value of inventory at the end of quarter t for firm i (INV_{it}) divided by the quarterly cost of goods (COGS_{it}) sold times the number of days in a quarter (i.e. 91 days). Inventory slack, which represents how much inventory is held relative to what is needed to meet the expected demand, is equivalent to the days of inventory outstanding which is quantified as the average time that inventory is held by the retailer before it is sold. To control for industry differences, the inventory slack levels were centered and standardized within each two-digit SIC industry group. In the examination of the

relationship between quarterly changes in slack and performance, we utilize the difference between the start of quarter and start of the next quarter inventory slack within a firm. Explicitly, inventory slack is calculated as:

$$\text{INVSLACK}_{it} = \frac{\text{INV}_{it}}{\text{COGS}_{it}} \times 91 \text{ days} \quad (1)$$

Hendricks et al. (2009) examined a firm's internal level of slack using the ratio of annual sales to net plant, property, and equipment (PPE). The ratio of firm sales to PPE was utilized also by Modi and Mishra (2011) as a measure of firm resource efficiency. As our study is focused on the relationships between slack and performance, it was concluded that the measures used should be intuitive to interpret, meaning that a measure of slack should be calculated such that as a firm becomes leaner, the value of the measure should decrease. The resource efficiency ratio used by Hendricks et al. (2009) and Modi and Mishra (2011) responds in the opposite direction; therefore, consistent with Kovach et al. (2015) we measure capacity slack as the ratio of sales over the value of the firm's plant, property, and equipment. Hence, the second measure of operational slack is defined as:

Capacity Slack (CAPSLACK_{it}): for firm i is the ratio of the value of the firm's net Plant, Property, and Equipment at the end of quarter t (PPE_{it}) divided by the quarterly sales (SALES_{it}) (Kovach et al., 2015). The relationship between capacity slack and performance in our sample were observed to be non-linear in nature; therefore the natural log of capacity slack is used in this study's analyses (Osborne, 2005). As with inventory slack, we centered and standardized the capacity slack values within each two-digit SIC group and utilized the quarterly change in capacity slack in the difference analysis. Mathematically, capacity slack is calculated as:

$$\text{CAPSLACK}_{it} = \ln \left(\frac{\text{PPE}_{it}}{\text{SALES}_{it}} \right) \quad (2)$$

Fig. 1 depicts the operational slack measures over the time period encompassed by this study. Since 1980, the average inventory slack level has decreased while the average level of capacity slack has fluctuated.

To evaluate the effect of unstable demand on the relationship between operational slack and performance, we include a measure of market instability in our models. The instability measure, also utilized in Kovach et al. (2015) evaluates the volatility of sales within an industry:

Market Instability - (INST_{jt}): is calculated quarterly for each two-digit SIC group. Using quarterly-level data for the firms in our sample, we first employ the ARIMA X-12 Seasonal Adjustment Program to calculate the seasonally adjusted sales forecast for each two-digit SIC group (Findley et al., 1998). The seasonal index for quarter t and industry j , $S_{j,t}$, calculated via ARIMA X-12 using the aggregate sales data at the two-digit SIC level using a rolling window of the prior 20 quarters. Thus, instability for a quarter within an industry is calculated as the industry's maximum seasonal index experienced during the prior 20 quarters minus the minimum seasonal index. Explicitly:

$$\text{INST}_{jt} = \text{Max}(S_{j,t-20}, \dots, S_{j,t-1}) - \text{Min}(S_{j,t-20}, \dots, S_{j,t-1}) \quad (3)$$

3.3. Dependent measure

To examine a retail firm's relative market performance, we employ the stock-response modeling approach utilized by Modi and Mishra (2011) and Alan et al. (2014) in which they compare firms' stock market returns in excess of the return expectations predicted using the Fama and French (1993) model. Stock-response modeling compares the return predicted for a stock by the Fama-French model with the actual stock return to measure the unexplained portion of a stock return (i.e. the residuals). Unlike other accounting based performance measures, the unexplained stock return innately measures relative retail firm performance from a shareholder perspective. Additionally, return on assets, one of the

Table 5
Granger Causality Tests of changes in Operational Slack and ΔUSR_{it} .

Independent Variables	Test 1: $\Delta X \rightarrow \Delta Y$ (Dependent Variable = ΔUSR)			Test 2: $\Delta Y \rightarrow \Delta X$ (Dependent Variable = Δ Operational Slack)			
	[Lag $\Delta Y \rightarrow \Delta Y$] ΔUSR on Lagged ΔUSR Param. Est. (Std. Errors)	Lagged $\Delta INVSLACK$ [Lag $\Delta Y + \text{Lag } \Delta X \rightarrow \Delta Y$] ΔUSR on Lagged ΔUSR and $\Delta INVSLACK$ Param Est. (Std. Errors)	Lagged $\Delta CAPSLACK$ [Lag $\Delta Y + \text{Lag } \Delta X \rightarrow \Delta Y$] ΔUSR on Lagged ΔUSR and $\Delta CAPSLACK$ Param Est. (Std. Errors)	Lagged $\Delta INVSLACK$ [Lag $\Delta X \rightarrow \Delta X$] $\Delta INVSLACK$ on Lagged $\Delta INVSLACK$ Param Est. (Std. Errors)	[Lag $\Delta X + \text{Lag } \Delta Y \rightarrow \Delta X$] $\Delta INVSLACK$ on Lagged ΔUSR and $\Delta INVSLACK$ Param Est. (Std. Errors)	Lagged $\Delta CAPSLACK$ [Lag $\Delta X \rightarrow \Delta X$] $\Delta CAPSLACK$ on Lagged $\Delta CAPSLACK$ Param Est. (Std. Errors)	[Lag $\Delta X + \text{Lag } \Delta Y \rightarrow \Delta X$] $\Delta CAPSLACK$ on Lagged ΔUSR and $\Delta CAPSLACK$ Param Est. (Std. Errors)
Intercept:	−0.00401** (0.00145)	−0.00378** (0.00145)	−0.00297* (0.00145)	0.255* (0.119)	0.302* (0.121)	0.00595*** (0.000877)	0.00877*** (0.000907)
ΔUSR_{it-1}	−0.850*** (0.00539)	−0.850*** (0.00541)	−0.851*** (0.00546)		−0.0606 (0.336)		−0.00165 (0.00253)
ΔUSR_{it-2}	−0.649*** (0.00675)	−0.646*** (0.00677)	−0.648*** (0.00683)				
ΔUSR_{it-3}	−0.423*** (0.00672)	−0.421*** (0.00674)	−0.421*** (0.00678)				
ΔUSR_{it-4}	−0.197*** (0.00535)	−0.198*** (0.00537)	−0.198*** (0.00541)				
$\Delta INVSLACK_{it-1}$		−0.000713*** (0.00006)		−0.629*** (0.00468)	−0.614*** (0.00499)		
$\Delta INVSLACK_{it-2}$		−0.000458*** (0.00006)		−0.230*** (0.00468)	−0.248*** (0.00499)		
$\Delta CAPSLACK_{it-1}$			−0.112*** (0.00692)			−0.596*** (0.00401)	−0.609*** (0.00421)
$\Delta CAPSLACK_{it-2}$			−0.0910*** (0.00741)			−0.510*** (0.00427)	−0.519*** (0.00450)
$\Delta CAPSLACK_{it-3}$			−0.0504*** (0.00693)			−0.567*** (0.00398)	−0.579*** (0.00418)
F test:	6222***	4146***	3519***	9303***	5110***	11,495**	8147***

*** $p < .001$, ** $p < .01$, * $p < .05$.

Table 6
Summary of Test Results.

Hypothesis	Measure	Finding(s)	Analysis
1a	Inventory Slack	Supported (Linear)	Firm-levels of Operational Slack
1b	Capacity Slack	Supported (Non-Linear Diminishing Returns)	
2a	Inventory Slack x Instability	Supported	Quarterly Difference in Operational Slack within Firms
2b	Capacity Slack x Instability	Supported	
3a	Δ Inventory Slack	Supported, with Granger causality in expected direction.	
3b	Δ Capacity Slack	Supported, with Granger causality in expected direction.	
4a	Δ Inventory Slack x Instability	Not Supported.	
4b	Δ Capacity Slack x Instability	Not Supported.	

more commonly employed accounting performance measures, has been shown to be unaffected by lean related inventory reductions (Callen et al., 2000), whereas unexplained stock returns and inventory and capacity changes have been linked in prior studies (Modi and Mishra, 2011).

As the predictor variables are measured internally by firms and only publicly released at the end of each quarter, we foresee that there will be a lag in the stock market's reaction and consequently examine the association between the current quarterly unexplained stock return and changes in the previous quarter for the predictor variables (Kesavan and Mani, 2013). Explicitly, we measure:

Unexplained Stock Return (USR_{it}): is equal to the actual stock return for firm i in quarter t (ASR_{it}) minus the expected stock return (SR_t) predicted using the Fama-French three factor model. Our quarterly dataset precluded the usage of the four or five factor versions of the Fama-French models as the additional factors are not available at the quarterly level. The expected return for a firm in a quarter was predicted using an unbalanced panel regression model using that quarter's Fama-French factors as predictors (i.e. *SMB* [Small minus Big], *HML* [High minus Low], and *[Rm − Rf]* [the excess return of the market]) (French, 2016). The difference between the actual quarterly stock return and the predicted quarterly return is designated as the unexplained quarterly stock return (USR_{it}):

$$USR_{it} = ASR_{it} - SR_t \quad (4)$$

where:

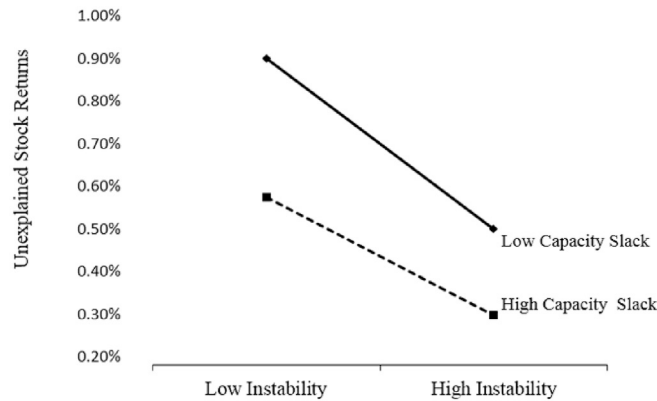
$$SR_t = a + \beta_1(SMB_t) + \beta_2(HML_t) + \beta_3([Rm - Rf]_t) + e_t \quad (5)$$

This approach has been previously employed in the literature to evaluate the impact of management actions on firm stock performance (Krasnikov et al., 2009; Mizik and Jacobson, 2008; Modi and Mishra, 2011). To compensate for industry specific variations in stock performance, we centered and standardized the unexplained stock return within each two-digit SIC group before conducting our analyses. However, as a robustness check, each of our models was also evaluated using the raw un-centered unexplained quarterly stock returns. For the quarterly difference analysis, we utilize the quarterly change in *USR* as the dependent variable.

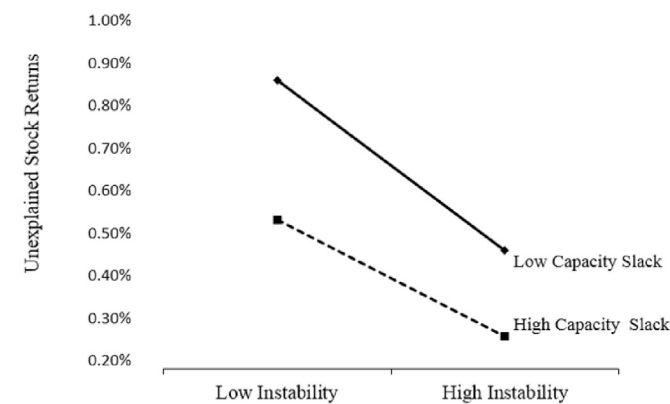
3.4. Control measures

In the retail industry, firms can trade-off between various equally

(a) Inventory Slack Level and Instability



(b) Capacity Slack Level and Instability

Fig. 3. Interaction Plots (± 1 Standard Deviation).

effective combinations of inventory turnover and gross margin. Gaur et al. (2014) and Hancerliogullari et al. (2016) show that retailers with high gross margins have lower inventory turnover and vice versa—a phenomenon that is referred to in the trade as “earn vs. turns.” Relatedly, Alan et al. (2014) find that inventory turnover is associated with stock market returns but only after adjusting for gross margins and capital intensity—i.e. in itself, lower inventory does not yield higher returns. To control for the possible effects that a firm's gross margin (*GM*) might have on the relationships of interest in this study, we include *GM* as a control variable in our models.

The measure of inventory slack included in our models, represents one of the three components of the Cash Conversion Cycle (*CCC*). The *CCC*, calculated as the average days required to receive payment from customers (typically designated as the days of receivables outstanding) plus the average days in which goods are held in inventory (which is the inventory slack measure described above) minus the average days that a firm takes to pay a supplier for goods and services (referred to as the days of payables outstanding), represents the amount of time that a firm takes to convert supplier purchases into cash receipts from customers (Farris and Hutchison, 2002, 2003). As all three of the components of the *CCC* are levers used by firms to manipulate their cash flows, we include both days of payables outstanding (*DPO*) and days of sales outstanding (*DSO*) as controls in our analyses.

We include firm size and leverage as additional controls in our model. Firm size, which is controlled for by incorporating total assets (*SIZE*) as a control in our model, has been shown previously to significantly impact firm market performance (Dowell et al., 2000; King and Lenox, 2002). The total asset levels for the firms in our sample were observed to be

non-linearly related to the dependent variable; therefore, we transform total assets and include its natural log in the model. Prior studies have shown that firms with high debt loads may be required to divert portions of their cash flows to meet their debt obligations (Capon et al., 1990), therefore we include leverage (*LEV*) in our model to control for the effect of debt loading on firm market performance (McConnell and Servaes, 1995). Additionally, a binary indicator variable (*RECESS*) is used to control for the impact of economic recessions on the relations of interest. *RECESS* is set equal to 1 during any quarter in which the U.S. economy experienced an economic recession. During the 140 quarters included in the 1980 to 2014 timeframe examined in this study, the U.S. economy experienced 5 separate recessions that impacted 23 calendar quarters (National Bureau of Economic Research, 2016).

3.5. Empirical model specification

Given the longitudinal nature of our data, we conduct panel regression analyses to evaluate the hypotheses. Unlike an Ordinary Least Squares (*OLS*) analysis, this approach compensates for the effects of time over our sample frame (Maddala and Lahiri, 1992).

The first model, which evaluates the relationships between operational slack and firm performance across the entire sample frame (i.e. H1a and H1b), is expressed as:

$$USR_{it+1} = \beta_0 + \beta_1(SIZE_{it}) + \beta_2(LEV_{it}) + \beta_3(RECESS_t) + \beta_4(INST_t) + \beta_5(GM_{it}) + \beta_6(DSO_{it}) + \beta_7(DPO_{it}) + \beta_8(INVSLACK_{it}) + \beta_9(CAPSLACK_{it}) + \varepsilon_{it} \quad (6)$$

As discussed, recent literature has found that the relationship between some measures of slack and performance is non-linear and best described by an inverted u-shaped curve, implying that the returns associated with improvements in slack diminish beyond an optimal point (Eroglu and Hofer, 2011; Isaksson and Seifert, 2014; Modi and Mishra, 2011; Kesavan and Mani, 2013.) To evaluate if optimal levels of slack exist for inventory and capacity slack in our retail context, the second model introduces a quadratic (i.e. squared) term for each measure of slack. When interpreting the results of this model, a linear relationship can be assumed if parameter estimate for a slack variable is significant and the corresponding squared term is insignificant. In contrast, if the squared term is significant, a negative parameter estimate suggests the existence of a non-linear inverted u-shaped relationship with a point of optimality (Eroglu and Hofer, 2011). This model is specified as:

$$USR_{it+1} = \beta_0 + \beta_1(SIZE_{it}) + \beta_2(LEV_{it}) + \beta_3(RECESS_t) + \beta_4(INST_t) + \beta_5(GM_{it}) + \beta_6(DSO_{it}) + \beta_7(DPO_{it}) + \beta_8(INVSLACK_{it}) + \beta_9(CAPSLACK_{it}) + \beta_{10}(INVSLACK_{it})^2 + \beta_{11}(CAPSLACK_{it})^2 + \varepsilon_{it} \quad (7)$$

The third model, which examines the impact of market instability on the relationship between operational slack and performance, expands on the first model and introduces terms to test the interactions between market instability and the slack measures. This model is expressed as:

$$USR_{it+1} = \beta_0 + \beta_1(SIZE_{it}) + \beta_2(LEV_{it}) + \beta_3(RECESS_t) + \beta_4(INST_t) + \beta_5(GM_{it}) + \beta_6(DSO_{it}) + \beta_7(DPO_{it}) + \beta_8(INVSLACK_{it}) + \beta_9(CAPSLACK_{it}) + \beta_{10}(INVSLACK_{it} \times INST_t) + \beta_{11}(CAPSLACK_{it} \times INST_t) + \varepsilon_{it} \quad (8)$$

The fourth model examines the relationships between quarterly changes in operational slack and changes in performance. Building on this model, the fifth model examines the impact of market instability on these relationships. The specifications for these models are:

$$\Delta USR_{it+1} = \beta_0 + \beta_1(\Delta SIZE_{it}) + \beta_2(\Delta LEV_{it}) + \beta_3(\Delta RECESS_t) + \beta_4(\Delta INST_t) + \beta_5(\Delta GM_{it}) + \beta_6(\Delta DSO_{it}) + \beta_7(\Delta DPO_{it}) + \beta_8(\Delta INVSLACK_{it}) + \beta_9(\Delta CAPSLACK_{it}) + \varepsilon_{it} \quad (9)$$

$$\Delta USR_{it+1} = \beta_0 + \beta_1(\Delta SIZE_{it}) + \beta_2(\Delta LEV_{it}) + \beta_3(\Delta RECESS_t) + \beta_4(\Delta INST_t) + \beta_5(\Delta GM_{it}) + \beta_6(\Delta DSO_{it}) + \beta_7(\Delta DPO_{it}) + \beta_8(\Delta INVSLACK_{it}) + \beta_9(\Delta CAPSLACK_{it}) + \beta_{10}(\Delta INVSLACK_{it} \times \Delta INST_t) + \beta_{11}(\Delta CAPSLACK_{it} \times \Delta INST_t) + \varepsilon_{it} \quad (10)$$

Though statistical methods cannot prove the existence of causal relationships, analyses which examine the relationships between a dependent variable and time-lagged independent predictor variables can be used to find support for or against the existence of causal relationships (Granger, 1969; Hult et al., 2008). To evaluate if causal relationships potentially exist in our models, we employ post-hoc Granger causality tests of relationships which are found to be significant in our tests of H3a and H3b. A predictor variable X is said to “Granger cause” a dependent variable Y if, (i) time-lagged values of a variable (X_{t-1}) significantly predict the present value of the dependent variable (Y_t) in the presence of lagged values of the dependent variable ($Y_{t-1} \dots Y_{t-n}$) and (ii) the reverse relationship is not found to exist (i.e. Y_{t-1} does not help predict X_t in the presence of $[X_{t-1} \dots X_{t-n}]$). As prescribed by Granger (1969), the models to test for causality should include successive time lagged values of the dependent variable (Y_t) as long as their effect is significant. Once the number of significant lagged values of the dependent variable to include is determined, lagged values of the predictor variable (X_{t-1}) are then introduced into the models. The reverse model (i.e. X_t and Y_t are swapped) is then tested using the same two-step process. A comparison of the two models will determine if Granger causality exists. It is important to note that true causality cannot be proven with Granger tests and that other unobserved variables may be impacting the relationships of interest. For parsimony, the model specifications for the Granger causality tests are not presented.

4. Empirical analysis and results

The results of the longitudinal panel analyses are presented in Tables 3–5. Table 6 summarizes the hypothesis tests. The models in this study were evaluated using STATA 14 due to the program's capability to evaluate unbalanced panel models. Hausman tests and F-tests were conducted for each version of the respective models to determine the appropriateness of a random effects or fixed effects approach (Greene, 2008). For all of the models, the Hausman tests showed the unique errors to be significantly correlated with the regressors, which indicates the presence of fixed effects. Additionally, the F-tests were significant for each model, which indicates the appropriateness a fixed effects model over a pooled ordinary least squares analysis (Baum, 2001). Based on these results, fixed effects versions of the models were utilized to test each of our hypotheses. The models' specifications, which utilize lagged predictor variables, mitigates the potential for multicollinearity; however, to verify that our findings are not substantively influenced by multicollinearity we calculated the Variance Inflation Factors (VIF) for each of our models and found that all of the VIF scores are less than 1.5, well below the recommended threshold of 10 (Cohen et al., 2003). To validate the robustness of the analyses, the models were also evaluated using the firms' raw USR_{it} values (i.e. not centered by industry) as the dependent variable. In these tests, the sign and significance of each relationship of interest was consistent with the results of the analyses utilizing the industry centered dependent variable.

Table 3 presents the results of the analysis of operational slack. The second column of the table illustrates that over the entire sample period, lower levels of both inventory and capacity slack are significantly associated with higher firm performance. These findings provide support for H1a and H1b.

The third column of Table 3 expands upon the initial analysis to investigate if optimal points exist for each type of operational slack. As discussed in Modi and Mishra (2011), findings would suggest that the performance improvements related to improvements in slack diminish if, for a given slack factor, the squared term's coefficient is significant and negative. For inventory slack (depicted in Fig. 2a), only the main effect is significant, which suggests a linear relationship with performance. In contrast, capacity slack meets the mathematical criteria indicating an inverted u-shaped relationship with a point of optimality. However, when examining the relationship in detail, the point of optimality (i.e. the point below which performance begins to diminish as slack

decreases) occurs approximately 5.5 standard deviations below the sample's mean centered capacity slack level (i.e. zero) – which indicates that over 99.99% of quarterly capacity slack levels in our sample lie to the right of the point of optimality. This implies that as capacity slack decreases, firm performance still increases for virtually every firm in our sample (though the level of the performance increase diminishes as a firm's level of slack decreases towards the point of optimality). For clarity, the relationship between capacity slack and performance for the 99th percentile of the quarterly firm capacity slack levels in our sample (i.e. $\pm 2.58 \sigma$) are depicted in Fig. 2b.

Column 4 in Table 3 examines if firms with more operational slack exhibit better performance when facing an unstable demand environment. An examination of the interaction effects between instability and the slack factors finds significant positive relationships between both measures and firm performance. These results indicate that demand instability does moderate the relationship between operational slack and firm performance. These results support the predictions of H2a and H2b.

We find support for H3a and H3b as reductions in inventory and capacity slack are both significantly associated with improvements in retail firm performance (Table 4, Column 2). The results of the post-hoc Granger causality analysis are presented in Table 5. This analysis tests if changes in capacity slack and inventory slack Granger cause changes in firm performance. The results show that lagged changes in both capacity slack and inventory slack significantly associate with changes in firm performance, while lagged values of firm performance are not significantly related to changes in capacity slack or inventory slack. These findings further strengthen H3a and H3b as they support the supposition that reductions in inventory slack and capacity slack both Granger cause improvements in firm performance.

Finally, we examine whether demand instability moderates the relationship between quarterly differences in operational slack and subsequent changes in performance (Table 4, Column 3). We do not find evidence that instability moderates the impact of changes in inventory or capacity slack levels on performance (H4a and H4b).

5. Discussion, contributions, limitations and future research

In the introduction, we pointed out that lean is a seminal theory in OM/SCM. Two propositions related to lean which have been explored in the literature, are that lower levels of both inventory and capacity slack positively contribute to performance. While these propositions are largely believed to be true in a variety of industries, in Section 2 we highlighted that other researchers have proposed countervailing thinking for retail—for example, the idea that in-store inventory drives sales. Thus, the key contribution of our paper is to show that lean theory does hold well in the retail industry. From both a snapshot and quarterly difference perspective and regardless of whether we look at capacity slack or inventory slack, lean produces superior, lasting returns for retailers.

In retail, other researchers (Alan et al., 2014) have shown that inventory predicts performance when it is adjusted for gross margin - i.e. these researchers have applied the classic newsvendor model to the aggregate (firm) level. We agree that retail managers should consider product gross margins when determining inventory policies. However, our results show that lower inventory generates higher firm performance regardless of gross margin (i.e. gross margin is a control variable in our models). From a lean theory testing standpoint, this is an important contribution. Testing for boundary conditions of theories is a key element of the knowledge building process, and our study shows that the retail domain appears to be well within the boundaries of lean - without qualifications. From a practitioner point of view, a conventional rule of thumb in lean thinking is that inventory slack is an “evil.” Thus, a contribution to practice is demonstrating that this broad principle is not limited to manufacturing, but instead serves the retail world very well.

Moreover, our quarterly difference analysis (supporting H3) backed with the Granger causality analyses enhances confidence in extant

research regarding these constructs and their linkage to performance (Granger, 1969; Hult et al., 2008). Our quarterly difference analysis also answers the question that practitioners are most interested in—i.e. “Will lean improve performance at my company?” This is certainly a fair question for practitioners to ask in light of the number of lean implementations that have not produced the results that were hoped for (Bhasin, 2008; Bortolotti et al., 2015; Pedersen and Huniche, 2011). We show that both reductions in inventory slack and reductions in capacity slack in one quarter significantly improve a firm's market performance in the following quarter. These results pair well with Alan et al. (2014), who show that portfolios of firms with high turnover relative to their peers yield higher future returns. Our research differs from Alan et al.'s in that our unit of analysis is individual firms, rather than portfolios, and our independent variable is inventory slack (i.e. leanness), rather than inventory turnover (the latter being a function of inventory and sales and thus less under the direct control of operations managers, who have relatively less control over sales). These findings serve investors because they speak strongly to front line managers by exploring variables over which the managers have the most control — i.e. changes in inventory at their particular organization.

Our finding of a linear relationship between inventory slack and performance (Fig. 2a) runs counter to studies showing non-linear relationships in manufacturing. Diverging results could be due to two characteristics of retail inventories versus manufacturing inventories: First, vendor owned inventories are more common in retail (Marquès et al., 2010). Second, retailers typically deal only with finished goods; while manufacturing inventories consist of raw materials, work in process, as well as finished goods. By contrast, the finding of a non-linear relationship between capacity slack and performance (H1b) aligns with recent studies of manufacturers (e.g. Eroglu and Hofer, 2011; Isaksson and Seifert, 2014; Kesavan and Mani, 2013), and it demonstrates the robustness of the slack-performance relationship for capacity levels across both the manufacturing and retail industries. However, as highlighted in the previous section, most retailers in our sample have capacity slack levels which are sufficiently high, such that extreme reductions would be required before performance would be expected to degrade.

Studies in a variety of contexts have examined whether market instability moderates the relationship between slack and performance. In our data, this moderating effect is fairly circumscribed. The cross-sectional analysis (H2a and H2b) does show a significant moderation effect for both inventory slack and capacity slack. However, from a practical standpoint, the benefit of having more slack only appears during periods of extreme instability - i.e. although Fig. 3a and b depict a statistically significant interaction effect, a level of slack one standard deviation above the mean only results in superior performance for levels of demand instability 3.7 and 4.3 standard deviations above the mean, respectively for inventory and capacity slack. Note that demand instability was never this high in any two-digit SIC retail industry across our 35 years of data. Thus, the advantages of slack seem more theoretical than practical in this context. The message to retail managers is that market instability will lessen the performance gap between the lean and non-lean firms; however, leaner retail firms will still typically outperform their non-lean competitors regardless of instability. The evidence for instability is even weaker in our quarterly difference analyses (H4a and H4b). These results are consistent with Kesavan et al. (2016) which find that high inventory turnover retailers expand more effectively to macro and firm level demand shocks than lower inventory turnover retailers. An important limitation to note of our analysis is that market instability was conceptualized as sales instability - i.e. volatility relative to historical sales. A worthwhile extension would be to utilize other measures of sales instability or to examine other types of uncertainty altogether, such as supply market volatility or environmental uncertainty.

Our findings definitively show that lower levels of inventory and capacity slack, as well as reductions in both slack measures over a

calendar quarter associate with better firm performance; while important, these results respectively represent analyses of snapshot levels and short-term reductions of operational slack. An important additional consideration is how these findings impact firms in the long-term. The longer-term performance implications of operational slack can be deduced by considering the results of our two analyses in concert with the Granger causality tests. First, building on the finding that quarterly reductions in operational slack improve market performance, the Granger tests show that reductions in inventory slack continue to relate to market performance improvements into the second quarter after the reduction, while reductions in capacity slack associate with market performance improvements for three quarters. Second, though reductions in capacity slack associate with improved performance over three quarters, the return from these reductions diminish as capacity slack levels decrease. The finding that inventory slack does not have a point of optimality has a slightly different implication – this finding implies that a retail firm can continue to realize market performance improvements by reducing inventory levels theoretically to zero. While this proposition may initially seem spurious, the wide adoption of inventory shedding practices such as vendor managed inventories across the retail industry brings some legitimacy to the goal of zero inventory for retailers (Marquès et al., 2010).

A limitation of this research is that our sample consists of retail firms publicly traded on the U.S. stock markets. On the surface, this may seem to limit our findings in the context of today's global economy; however, many of these publicly traded firms are global companies with expansive operations, which lead us to believe that our results will hold for retailers that are global in nature, regardless of the location of their corporate headquarters.

A natural extension of our study would be to measure and examine the impacts of supply chain wide lean management programs that encompass coordinated efforts across multiple members of a supply chain, versus this study's examination of individual firm behavior. An empirical study examining the relationship between the performance of an individual retailer and the lean management policies of partner vendors would shed further light on the complexities of lean management for supply chain firms. There are also numerous opportunities to extend our study to examine the robustness of our findings across industries with less tangible supply chains (e.g., services). With the increasing focus on service supply chains, the applicability of lean management strategies to these industries will be of great interest to practitioners.

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