BRAND POWER MEETS MARKET FEAR

A DOWNSIDE RISK PERSPECTIVE

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Brand Power Meets Market Fear: A Downside Risk Perspective

Abstract:

Brand equity represents an important intangible asset, yet its link to market behavior in negative-return months remains insufficiently understood. Understanding whether brand equity mitigates this so-called downside risk has implications for valuation, portfolio construction and corporate strategy. Despite its attention in contemporary discussions, there is no overarching measure of both downside risk and brand equity. We apply a novel measure of brand equity and a threefold framework to measure downside risk. We find an association between brand equity and downside risk, depending on the measure of downside risk and the portfolio-weighting scheme. Further, we show that crises affect this relationship non-universally. Also, strong brands tend to lower B2C firms' risk and partly offset the inherent risk we identify of following a B2B strategy. We consider various robustness tests and show that they do not materially invalidate our key results.

Keywords:

Brand Equity, Downside Risk, Crisis Moderation, Business Model, Intangible Assets

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1 Introduction

Brand equity and downside risk are concepts with unclear and often inconsistent definitions. Yet, managers and investors confront both on a daily basis, whether in strategic brand decisions or in financial market evaluations. Despite this practical relevance, we still lack a clear understanding of how to measure them and how brand equity relates to firms' downside risk. Therefore, we address this ambiguity by using output-facing methods for measuring brands and combining them with established approaches for estimating downside risk. From this, the main contribution of this paper is to analyze the relationship between brand equity and downside risk and to present an understanding of how crisis types and business models affect this interaction. In our analysis, we observe that the relationship between downside risk and brand equity is not universal. Instead, whether an effect appears depends on the specific downside risk measure, the underlying crisis mechanism and the firm's business model. Throughout the analysis, we also observe value-weighted portfolios exhibiting higher downside risk, whereas equal-weighted portfolios can be associated with lower downside risk. We additionally find support that strong B2B firms show to have an embedded higher downside risk than strong B2C firms. Further, we show that downside risk patterns differ when the analysis is performed at the portfolio- or firm-level, and that results vary with how brands are measured.

In today's knowledge-driven economy, the composition of corporate value has undergone a fundamental transformation. The Asset Management Council (Heidi, 2024) highlights this by stating that intangible assets, such as intellectual property, recently outweigh traditional tangible assets in determining firm value. This shift emphasizes that value creation now relies more on non-physical resources to strengthen customer loyalty and secure long-term competitiveness. For instance, the ratio of intangible assets to enterprise value for the FAANG[1] companies and the largest global players is around 90% (*Corporate Intangible Assets Grew to USD 61.9 trillion in 2023,*).

Among intangible assets, brand capital stands out as one of the most visible and financially relevant drivers of firm value. One of the most influential studies linking brand value to firm performance is Belo, Lin, and Vitorino (2014). They conceptualize brand capital as the stock of intangible assets accumulated through firms' past marketing and advertising investments. Belo et al. (2014) find that firms with such elevated brand capital enjoy lower volatility in revenues and higher valuations relative to peers. Therefore, their findings position brand capital as a distinct productive asset that influences both firm risk and expected returns.

Strong brands exhibit a competitive advantage since they enhance customer loyalty, reduce price sensitivity and support stable and recurring cash flows (Keller, 2013). However, brands have an inherent difficulty to being measured at their true economic value, as their value cannot directly be observed due to the lack of market prices. Furthermore, conventional accounting systems fail to capture brand value since most marketing or innovation expenditures are treated as expenses rather than capitalized investments. Additionally, they are inconsistently disclosed or are strategically reported (Lev and Gu, 2016; Shi, Grewal, and Sridhar, 2021). This underscores that they remain difficult to be measured and compared accurately.

Recent advances attempt to address these limitations through output-based measures of brand equity. A key contribution is by Boustanifar and Kang (2025) who propose

1. FAANG refers to Facebook (Meta), Apple, Amazon, Netflix and Google (Alphabet).

two methods to measure brand equity. They use a third-party provider ranking brands annually, which is called Interbrand, and a text-based brand frequency metric from SEC annual filings. The authors argue for their method by showing that traditional input-based proxies such as advertising expenditures do not reliably predict higher excess returns. Their results show that strong brand firms earn annual excess returns of 2.2 - 3% from the year 2000 until 2020. Their findings suggest that brand capital is not only a source of firm value, but may also be systematically mispriced in equity markets. Moreover, while they note that brand reputation shapes investor perceptions across varying market conditions, their core analysis focuses on full-sample average annual excess returns. Although they broadly assess distinct sub-periods, they do not evaluate whether strong brands provide lower risk during downside markets, periods when such effects are likely to matter most. In this thesis, we define downside markets as months in which the market excess return is negative.

This missing link is crucial. While recent research has shown how brands influence firms' average performance, considerably less is understood about their relationship with downside risk. Rego, Billett, and Morgan (2009) provide early evidence that firms with high brand equity tend to experience lower credit risk during downside market months. However, this finding is based on aggregated survey downside market data between the years 2000 and 2006. Further research supports this possible stabilizing role. Lou (2014) finds that increased advertising activity can raise investor attention and mitigate stock price declines following shocks. Yet, Lou (2014) examines periods as a whole and does not distinguish between market conditions nor adverse effects such as crises. McAlister, Srinivasan, and Kim (2007) provide further evidence that brand-related investments, particularly advertising, reduce firms' exposure to systematic risk. In particular, these investments influence risk profiles by stabilizing demand, moderating revenue volatility and reducing sensitivity to market-wide shocks. This supports the idea that brand capital has a risk-mitigating role beyond its effect on returns.

Cross-crisis analyses are a dimension that could benefit from further exploration in brand contexts. Research in macro-finance shows that crises differ in their underlying mechanisms, such as credit contraction, demand collapse, uncertainty shocks or liquidity freezes (Claessens and Kose, 2013). This implies that firms are not uniformly affected across crises and that the relationship of brand equity and downside risk may vary depending on the structure of the shock. To examine the relationship, we follow established crisis definitions from prior research that best capture the crisis dynamics from a US market perspective. Kinal and Kinal (2022) define the Dotcom crisis as spanning March 2000 to October 2002, a period marked by the collapse of technology valuations. Ofek and Richardson (2003) further examine the buildup of the bubble and its burst in early 2000, providing additional insight into the dynamics of this episode. The Global Financial Crisis can be defined as spanning from August 2007 to March 2009 as a period capturing the escalation of credit market stress and systemic failures in financial institutions (Fahlenbrach and Stulz, 2011). The COVID-19 crisis window in our study follows Baek, Mohanty, and Glambosky (2020). They analyze the early phase of the COVID-19 pandemic using industry-level volatility data from the first months of 2020. They focus on the period of heightened uncertainty, from which we define the COVID-19 crisis window as January to April 2020. Finally, we define the energy shock crisis from June 2021 to December 2022, based on the *Annual Economic Report 2022* (2022). The report attributes the sustained inflationary shock to rising energy prices, supply disruptions and geopolitical tensions. Using these well-established definitions ensures that our crisis periods align with earlier

empirical work and reflect the dominant mechanisms characterizing each shock.

A further critical point that has been debated in brand research concerns the role of business models in shaping how brands create value. Previous work shows that business models fundamentally influence customer relationships and therefore suggests that brand equity does not operate uniformly across business-facing and consumer-facing firms. Ulaga and Eggert (2006) show that B2B value is created through long-term partnerships, interdependence and service performance. They also highlight that supplier reputation functions as a signal of reliability and reduced transactional risk. In line with this distinction, Lindgreen and Wynstra (2005) summarize prior consumer research showing that value in consumer markets is often driven by individual perceptions, emotional attachment and brand-based differentiation. However, their own analysis emphasizes that B2B value is more functional and relational. Kowalkowski, Kindström, and Brehmer (2011) demonstrate that industrial (B2B) offerings are evaluated using technical criteria and professional decision processes. Vargo and Lusch (2004) argue that value creation mechanisms differ depending on how customers engage with the firm, reinforcing the idea that the way brands generate value is contingent on the underlying business model. Finally, Homburg, Jensen, and Krohmer (2008) document structural differences in how firms organize marketing and customer interaction across industries, some of which correspond to consumer-facing versus business-facing contexts. This supports the view that brand equity functions differently depending on the firm's market orientation. Together, these findings suggest that the role and effectiveness of brand equity vary systematically across business-facing, consumer-facing and hybrid firms.

Practically, this paper classifies firms based on previously established literature on business model typologies (Teece, 2010; Zott, Amit, and Massa, 2011; Iankova, Davies, Archer-Brown, Marder, and Yau, 2019). The classification builds a framework of each firm's primary customer type, brand communication, industry context and any events that materially changed its business mix over time. Examples of how each firm was classified, together with the reasoning behind these decisions, are provided in the appendix (A.4).

Despite significant progress in measuring brands and understanding their firm value relevance, prior research has not examined whether different types of crises or differing business models affect the relationship between brand equity and downside risk. This leaves an important gap in understanding how brand capital behaves under stress. Thus, this thesis examines whether stronger brand equity exhibits lower downside risk and whether this effect differs across distinct types of crises and business models.

Understanding this gap is highly relevant for investors and managers. Investors need to know whether brand equity could be associated with risk in crisis environments. Managers rely on brand equity to stabilize cash flows, justify marketing budgets and signal resilience to markets. Our contribution to previous research allows both academics and practitioners to extend their understanding of how brand equity relates to risk in downside markets. This makes the question both theoretically important and practically valuable.

2 Data Description and Descriptive Statistics

2.1 Interbrand Data

We derive the core dataset used in this study from Interbrand's Best Global Brands rankings (*Best Global Brands 2024 — Ranking,*). Interbrand publishes this ranking annually and has done so since the year 2000. The first edition included the top 75 global brands, after which the list expanded to the top 100 brands from 2001 onward. Although the 2025 ranking is already available, we exclude it in our analysis because the corresponding financial market data in WRDS is not yet accessible. We also assume the rankings from 2000 to be the same in the years 1998 and 1999 in order to construct 18-month rolling downside betas later in the analysis. We see this as a reasonable assumption, considering that on average, only two companies get dropped and added in the rankings yearly. Our sample therefore spans the period 1998 to 2024.

To construct a dataset that can be integrated with financial market information, we extract every brand and its year-specific ranking from the annual reports. Some brands, such as Coca-Cola and Microsoft, are consistently present throughout the sample period, while others enter or exit the ranking over time. We then match each brand to its U.S.-listed parent company by merging the Interbrand data with WRDS identifiers including PERMNO, GVKEY and CIK (*CRSP and Compustat: CRSP/Compustat Merged (CCM) Database,* 2025). We restrict the sample to brands whose ultimate parent company is publicly traded in the United States to ensure that the resulting portfolios are tradeable. We remove brands owned by non-U.S. parents from the dataset unless the brand originated as a U.S. asset before being acquired by a foreign company. We check all tickers manually and verify them through WRDS to ensure accurate parent-firm identification.

For each brand-year observation we also document any adjustments that were necessary due to mergers, acquisitions or other corporate events that affect brand ownership or classification. In an additional step, we merge several layers of industry classification data, including NAICS and the full GICS hierarchy (sector, group, industry and sub-industry), for both brands and their parent firms. This allows us to construct within-industry portfolios and to apply our classification of firms into consumer-facing, business-facing or hybrid business models. Therefore, we assign each brand to one of these categories on a reasoned basis. We refer to this constructed strong brand portfolio as the Interbrand portfolio.

2.2 Stock Universe

The stock universe serves as both our input to fill the Interbrand data with market specifiers and as our weak portfolio for the regressions we are running.

We build the stock universe by merging the CRSP/Compustat Merged Fundamentals Monthly File and the CRSP Monthly Stock File (*CRSP and Compustat: CRSP/Compustat Merged (CCM) Database,* 2025). The CCM panel provides firm-level accounting data, linking Compustat fundamentals with market identifiers from CRSP. The monthly stock file supplies monthly stock-level data for all securities listed on U.S. exchanges. We export both datasets directly from WRDS and cover the period from 1998 to 2024. The merge yields a panel of U.S. publicly listed firms containing monthly observations of returns, market capitalization and key balance sheet variables.

To ensure consistency across analyses, we restrict the sample to common shares, use main exchanges and incorporate delisting returns to capture total returns. We ensure each observation to be uniquely identified by PERMNO, GVKEY and CIK, which enables the one-to-one linkage back to the Interbrand brand-parent mappings to build the strong brand portfolio. To ensure the exclusion of Interbrand firms in order to create the weak brand portfolio, we flag all Interbrand firms in the code with 1 and all others with 0. We also sort every entry into one of ten self-defined overarching industry groups by matching the firms by their NAICS-code. These entail Industrials, Consumer Discretionary, Financials, Consumer Staples, Business Services, Communication Services, Technology, Materials, Energy & Utilities and Healthcare. We perform a similar sort for classifying each company in the stock universe after its dominant business model with the help of the NAICS-code. Lastly, we also add the current market excess rate and risk-free rate for all timestamps by considering the 1-month US T-bill rate. The data for the risk-free rate comes from the official Fama French Library, which uses the ICE BofA US 1-Month Treasury Bill Index.

2.3 Descriptive Statistics

Table 1: Turnover of brands considered in the Interbrand portfolio 1998-2024

Year	**# of IB stocks**	**# added**	**% added**	**# dropped**	**% dropped**
1998	41.0				
1999	41.0	0.0	0.0	0.0	0.0
2000	41.0	0.0	0.0	0.0	0.0
2001	54.0	14.0	34.1	1.0	2.4
2002	56.0	6.0	11.1	4.0	7.4
2003	54.0	0.0	0.0	2.0	3.6
2004	51.0	2.0	3.7	5.0	9.3
2005	47.0	3.0	5.9	7.0	13.7
2006	47.0	1.0	2.1	1.0	2.1
2007	48.0	3.0	6.4	2.0	4.3
2008	47.0	5.0	10.4	6.0	12.5
2009	45.0	3.0	6.4	5.0	10.6
2010	46.0	2.0	4.4	1.0	2.2
2011	45.0	1.0	2.2	2.0	4.3
2012	48.0	3.0	6.7	0.0	0.0
2013	47.0	2.0	4.2	3.0	6.2
2014	47.0	1.0	2.1	1.0	2.1
2015	47.0	1.0	2.1	1.0	2.1
2016	47.0	2.0	4.3	2.0	4.3
2017	46.0	2.0	4.3	3.0	6.4
2018	45.0	0.0	0.0	1.0	2.2
2019	46.0	1.0	2.2	0.0	0.0
2020	45.0	2.0	4.3	3.0	6.5
2021	44.0	0.0	0.0	1.0	2.2
2022	42.0	1.0	2.3	3.0	6.8
2023	43.0	1.0	2.4	0.0	0.0
2024	43.0	2.0	4.7	2.0	4.7
Average	46.4	2.2	4.9	2.2	4.5

For each year, Table 1 reports the number of firms included in the Interbrand portfolio, the number and percentage of firms newly added and the number and percentage removed relative to the previous year. The average row reports the mean number of brands considered across the sample period.

Figure 1: Number of brands considered in the Interbrand portfolio 1998-2024

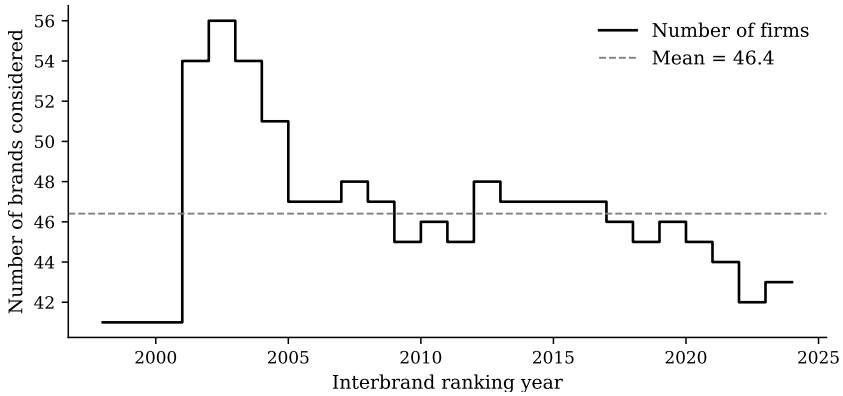


Figure 1 shows the number of brands included in the Interbrand portfolio from 1998 to 2024 and the average of the period.

Table 1 and Figure 1 show the number of brands included in the Interbrand ranking over time. The portfolio size fluctuates between approximately 40 to 56 firms, with an average of around 46 companies per year. The initial rise in the early 2000s reflects the expansion of Interbrand's coverage to 100 brands per year. The gradual decline thereafter is largely attributable to the increasing prominence of global brands headquartered outside the United States (e.g. Budweiser), as well as delistings and mergers among established U.S. firms.

Figure 2: Development of business model portfolio share in %

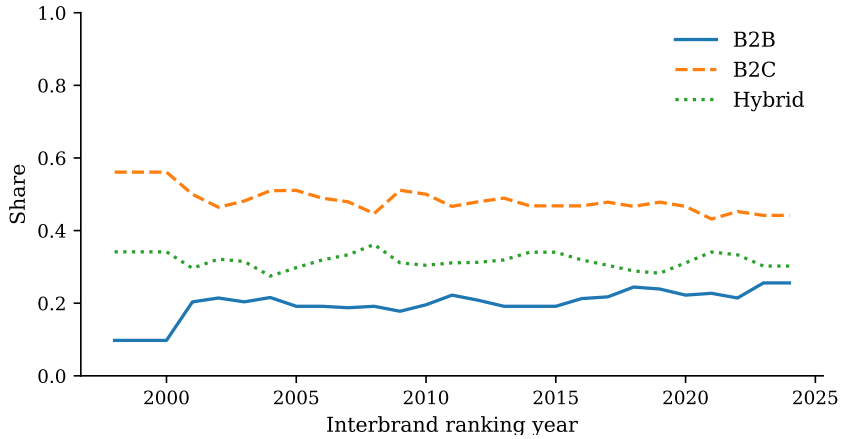


Figure 2 shows the share of B2B, B2C and hybrid firms in the Interbrand portfolio from 1998 to 2024.

Table 2: Overview of dominant business model for each brand in the Interbrand portfolio

Brand	Model	Brand	Model	Brand	Model
3M	B2B	GAP	B2C	Mobil	B2B
AIG	B2B	General Electric	B2B	Morgan Stanley	Hybrid
AOL	Hybrid	Gillette	B2C	Motorola	Hybrid
AT&T	Hybrid	Goldman Sachs	Hybrid	Netflix	B2C
Accenture	B2B	Google	Hybrid	Nike	B2C
Adobe	B2C	HP	Hybrid	Nvidia	B2B
Airbnb	B2C	HPE	B2B	Oracle	B2B
Amazon	B2C	Harley-Davidson	B2C	Pampers	B2C
American Express	Hybrid	Heinz	B2C	PayPal	B2C
Apple	B2C	Hertz	Hybrid	Pepsi	B2C
Avon	B2C	Hilton	Hybrid	Pfizer	B2B
Barbie	B2C	IBM	Hybrid	Pizza Hut	B2C
Boeing	B2B	Instagram	B2C	Ralph Lauren	B2C
Budweiser	B2C	Intel	B2B	Salesforce	B2B
Campbell's	B2C	J.P. Morgan	Hybrid	Starbucks	B2C
Caterpillar	B2B	Jack Daniel's	B2C	Sun Microsystems	B2B
Chevrolet	B2C	John Deere	B2B	Tesla	B2C
Cisco	B2B	Johnson & Johnson	Hybrid	Texas Instruments	B2B
Citi	Hybrid	KFC	B2C	Tiffany & Co.	B2C
Coca-Cola	B2C	Kellogg's	B2C	Time	Hybrid
Colgate	B2C	Kleenex	B2C	UPS	Hybrid
Compaq	Hybrid	Kodak	B2C	Uber	B2C
Dell	Hybrid	MTV	Hybrid	Visa	Hybrid
Discovery	B2C	Marlboro	B2C	Wall Street Journal	Hybrid
Disney	B2C	Marriott	B2C	Wrigley	B2C
Ebay	B2C	MasterCard	Hybrid	Xerox	B2B
Estée Lauder	B2C	McDonald's	B2C	Yahoo!	Hybrid
Facebook	B2C	Merck	B2B	Zoom	Hybrid
FedEx	Hybrid	Merrill Lynch	Hybrid		
Ford	B2C	Microsoft	Hybrid		

Table 2 lists all brands in the Interbrand portfolio from 1998 to 2024 along with their assigned business model. Each brand is classified based on its primary customer type, brand communication, and industry context, with firms assigned according to their predominant strategy over the years.

Figure 2 and Table 2 show the distribution of the three considered business models across time and brands. The results indicate that consumer-facing firms consistently dominate the portfolio. This ongoing dominance shows that companies with strong global brands, especially in technology, retail, and automotive, benefit from close consumer engagement. In contrast, B2B firms account for a smaller but stable share, while hybrid firms represent the remaining shares. The stable proportions over time suggest that Interbrand consistently values how visible a brand is to consumers and how well people recognize it.

Figure 3: Development of industry portfolio share in % (top 3)

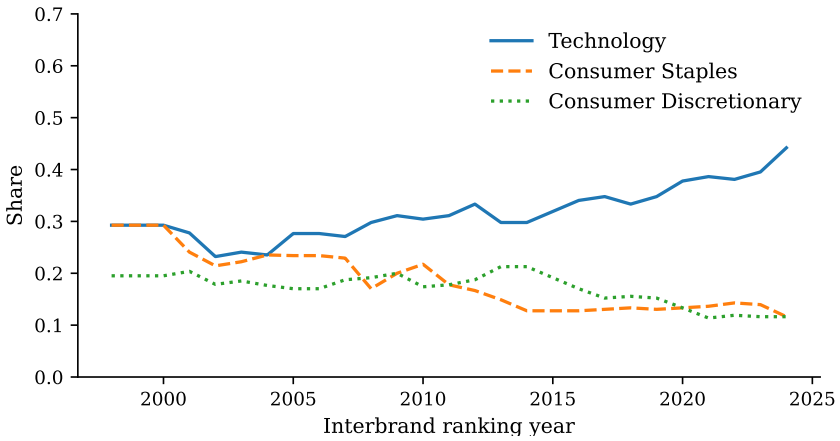


Figure 3 shows how the portfolio's industry composition has evolved for the top three sectors, expressed as each sector's percentage share of annual appearances in the Interbrand portfolio from 1998 to 2024.

Table 3: Overview of dominant industry for each brand in the Interbrand portfolio

Brand	**Ind.**	**Brand**	**Ind.**	**Brand**	**Ind.**
3M	Mat	GAP	CD	Mobil	EU
AIG	Fin	General Electric	Ind	Morgan Stanley	Fin
AOL	BS	Gillette	CS	Motorola	Tech
AT&T	Comm	Goldman Sachs	Fin	Netflix	Comm
Accenture	BS	Google	Tech	Nike	CD
Adobe	Tech	HP	Tech	Nvidia	Tech
Airbnb	Tech	HPE	BS	Oracle	Tech
Amazon	Tech	Harley-Davidson	CD	Pampers	CS
American Express	Fin	Heinz	CS	PayPal	Tech
Apple	Tech	Hertz	CD	Pepsi	CS
Avon	CS	Hilton	CD	Pfizer	HC
Barbie	CD	IBM	Tech	Pizza Hut	CD
Boeing	Ind	Instagram	Tech	Ralph Lauren	CD
Budweiser	CS	Intel	Tech	Salesforce	Tech
Campbell's	CS	J.P. Morgan	Fin	Starbucks	CD
Caterpillar	Ind	Jack Daniel's	CS	Sun Microsystems	Tech
Chevrolet	CD	John Deere	Ind	Tesla	Tech
Cisco	Tech	Johnson & Johnson	HC	Texas Instruments	Tech
Citi	Fin	KFC	CD	Tiffany & Co.	CD
Coca-Cola	CS	Kellogg's	CS	Time	BS
Colgate	CS	Kleenex	Ind	UPS	Ind
Compaq	Tech	Kodak	CS	Uber	Tech
Dell	Tech	MTV	Comm	Visa	Tech
Discovery	Comm	Marlboro	CS	Wall Street Journal	Comm
Disney	BS	Marriott	CD	Wrigley	CS
Ebay	BS	MasterCard	Tech	Xerox	Tech
Estée Lauder	CS	McDonald's	CD	Yahoo!	Tech
Facebook	Tech	Merck	HC	Zoom	Tech
FedEx	Ind	Merrill Lynch	Fin		
Ford	CD	Microsoft	Tech		

Table 3 lists all brands mentioned in the Interbrand rankings and their dominant industry. CS = Consumer Staples; CD = Consumer Discretionary; Tech = Technology; Fin = Financials; HC = Healthcare; Comm = Communication Services; Ind = Industrials; Mat = Materials; EU = Energy & Utilities; BS = Business Services.

Figure 3 and Table 3 show the distribution of the industries across time and brands. Figure 3 illustrates the development of portfolio composition by industry, focusing on the three most represented sectors, technology, consumer staples and consumer discretionary. The share of technology firms rises steadily over time, reaching over 40 percent toward the end of the sample period. Conversely, the share of consumer staples and consumer discretionary firms gradually declines. This increase reflects the growing dominance of technology-oriented firms. Table 3 provides an overview of the dominant industry classifications for all brands represented in the Interbrand portfolio over the period 1998-2024. The table groups each brand according to its primary industry, using broad sector categories.

Figure 4: Top 10 brands' market-cap share development in the value-weighted portfolio

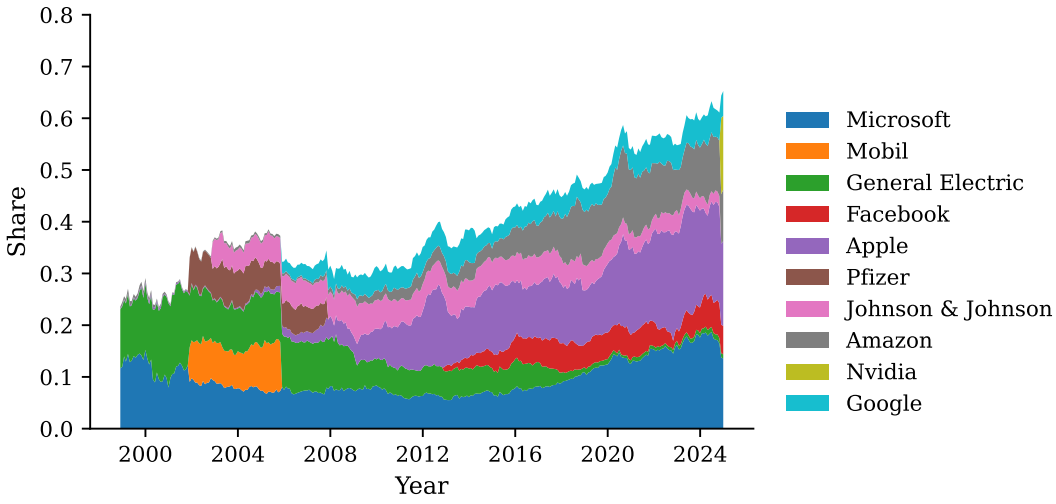


Figure 4 shows the evolution of the value-weighted portfolio share of the ten largest brands by market capitalization

In Figure 4, we observe that in later years, fewer firms make up a larger share of the value-weighted portfolio. Microsoft, Apple and Amazon have between 15-20% of the shares in the value-weighted portfolio. Additionally, we can observe that the firms that make up the largest share of the value-weighted portfolio are technology firms.

3 Methodology and Theoretical Framework

We make use of three complementary downside risk measures to get a broad perspective of downside risk. First, we use downside beta as defined by Ang, Chen, and Xing (2006). They show that beta can be divided up into upside and downside beta. Downside beta captures how strongly a portfolio or firm responds to market movements in months with negative market excess return. We calculate it using an 18-month rolling window in order to always be able to have the most precise estimate of downside beta, especially for the crisis analysis which we perform. As the underlying model, we use the Fama-French six-factor model, so that the beta we consider will be the downside market beta adjusted for the other systematic risk factors. Second, we consider downside excess return, that is the equity return minus the risk-free rate conditional on months when the market excess return

is negative. We define equity return as the total return earned by stakeholders through dividends yield and capital gains (Berk and DeMarzo, 2024). We acknowledge this not being a theoretically ideal way of testing for risk, but it shows relative risk for investors or managers. Third, we measure downside risk using a conditional semi-variance. In general, semi-variance is defined as the downside variance of returns and calculated as the expected squared shortfall below the mean (Estrada, 2002). We adjust this general definition as we are interested in months when the market excess return is negative. Therefore, we treat semi-variance as the average squared negative deviation of the portfolio's excess return from the market excess return in those months. This now captures the part of volatility that investors are most concerned about. Here again, we acknowledge that this method does not fully translate to risk, but can validly be used as an estimate. Because downside risk can manifest in different ways and each measure captures a distinct aspect of negative return behaviour, we use all three measures to ensure that our results are not driven by one single definition.

In order to measure brand equity in this paper, we will follow the approach presented by Boustanifar and Kang (2025). As they have shown that previous brand measures present imprecise results and their approach resembles economic reality, we see their approach as state-of-the-art in measuring brand equity. Therefore, we adopt an output-based approach in our study by using Interbrand's annual ranking as our primary measure of brand equity.

We create a portfolio from the Interbrand data, which we call our strong brand portfolio. This combines all brands and their respective public parent companies listed in the Interbrand annual rankings into one portfolio. As Interbrand publishes its ranking once a year in October, we assume the composition of the strong brand portfolio to remain constant from November until the end of October of the following year. We choose this method, as the strong brand portfolio can be understood to be tradeable starting November each year. From this, both yearly equal-weighted and value-weighted versions of the portfolio are constructed. We construct the value-weighted portfolio based on market capitalization.

To provide a meaningful benchmark and a portfolio to compare, we also construct a weak brand portfolio. This portfolio consists of all US-listed firms in our stock universe except for the public parent companies that hold brands listed in the Interbrand data. As this entails almost all stock-listed firms on the US market, we also refer to this portfolio as our market portfolio. Since we construct this weak brand portfolio through all parent companies not considered in the Interbrand ranking, the composition changes similarly on a yearly basis. We also create both yearly equal-weighted and value-weighted versions of the portfolio. This ensures direct comparability of the strong brand and weak brand portfolios.

Portfolio-based analysis is a central tool in empirical asset pricing, and characteristic-sorted portfolios such as those introduced by Fama and French (1993) are widely used to reduce noise and reveal systematic return patterns. We acknowledge that portfolio analysis has some limitations such as possible misleading results due to portfolios' strong covariance structure making many models overstate fit (Lewellen, Nagel, and Shanken, 2010). Therefore, we complement our analysis with firm-level models.

In order to control for systematic market risks in our study, we rely on the Fama-French Five Factor model extended with the momentum factor. Fama and French (1993, 2015) show that firm size, value orientation, profitability and investment behaviour ex-

plain important cross-sectional differences in returns. The momentum factor introduced by Carhart (1997) captures that firms with strong recent performance tend to continue outperforming in the short run.

Before proceeding with our own analyses, we start by replicating the main empirical result of Boustanifar and Kang (2025), namely the existence of a brand premium. This replication allows us to validate the quality and structure of our dataset. We deem this to be necessary as matching the brands with both their respective parent companies changing over the years and matching them with database identifiers is a manual process. By confirming the results, we establish a solid base for our subsequent analysis of brand equity and downside risk.

Now we will turn towards our main regressions. Using both portfolio-level and firm-level analysis, as well as three downside risk measures[2], allows us to closely evaluate how brand equity relates to downside risk under different market environments. Econometrically, our testing entails the following:

H1. A portfolio of firms with stronger brand equity exhibits a different level of downside risk than the overall market portfolio.

$$\begin{aligned} H_0 &: \ \beta_1 = 0 \\ H_1 &: \ \beta_1 \neq 0 \end{aligned}$$

$$\text{Downside risk}_{p,t} = \beta_0 + \beta_1 \, \text{SBP}_t + \varepsilon_{p,t} \qquad \text{(Portfolio-level)}$$

$$\text{Downside risk}_{i,t} = \beta_0 + \beta_1 \, \text{SBF}_{i,t} + \varepsilon_{i,t} \qquad \text{(Firm-level)}$$

H2. Crisis type moderates the relationship between brand equity and downside risk so that the effect differs across crisis categories.

$$\begin{aligned} H_0 &: \ \beta_6 = \beta_7 = \beta_8 = \beta_9 = 0. \\ H_1 &: \ \exists \, \beta_n \neq 0 \text{ for } n \in \{6, 7, 8, 9\} \end{aligned}$$

$$\begin{aligned} \text{Downside risk}_{p,t} = \beta_0 &+ \beta_1 \, \text{SBP}_t + \beta_2 \, \text{DotCom}_t + \beta_3 \, \text{GFC}_t + \beta_4 \, \text{COVID}_t \\ &+ \beta_5 \, \text{EnergyShock}_t + \beta_6 \, (\text{SBP}_t \times \text{DotCom}_t) + \beta_7 \, (\text{SBP}_t \times \text{GFC}_t) \\ &+ \beta_8 \, (\text{SBP}_t \times \text{COVID}_t) + \beta_9 \, (\text{SBP}_t \times \text{EnergyShock}_t) + \varepsilon_{p,t} \end{aligned} \qquad \text{(Portfolio-level)}$$

$$\begin{aligned} \text{Downside risk}_{i,t} = \beta_0 &+ \beta_1 \, \text{SBF}_{i,t} + \beta_2 \, \text{DotCom}_t + \beta_3 \, \text{GFC}_t + \beta_4 \, \text{COVID}_t \\ &+ \beta_5 \, \text{EnergyShock}_t + \beta_6 \, (\text{SBF}_{i,t} \times \text{DotCom}_t) + \beta_7 \, (\text{SBF}_{i,t} \times \text{GFC}_t) \\ &+ \beta_8 \, (\text{SBF}_{i,t} \times \text{COVID}_t) + \beta_9 \, (\text{SBF}_{i,t} \times \text{EnergyShock}_t) + \varepsilon_{i,t} \end{aligned} \qquad \text{(Firm-level)}$$

2. The appendix shows our model diagnostics (A.2)

H3. Business model moderates the relationship between brand equity and downside risk so that the effect of brand equity on downside risk differs across business-facing, consumer-facing and hybrid firms when examined on a firm-level.

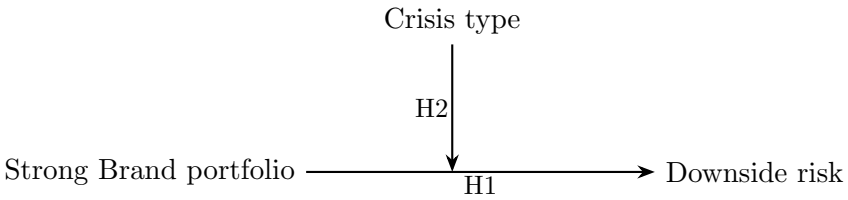
$$H_0 : \ \beta_4 = \beta_5 = 0$$
$$H_1 : \ \exists\, \beta_n \neq 0 \text{ for } n \in \{4, 5\}$$

$$\begin{aligned}\text{Downside risk}_{i,t} = \beta_0 &+ \beta_1\, \text{SBF}_{i,t} + \beta_2\, \text{B2B}_{i,t} + \beta_3\, \text{Hybrid}_{i,t} \\ &+ \beta_4\, (\text{SBF}_{i,t} \times \text{B2B}_{i,t}) + \beta_5\, (\text{SBF}_{i,t} \times \text{Hybrid}_{i,t}) + \varepsilon_{i,t}\end{aligned}$$

(Firm-level)

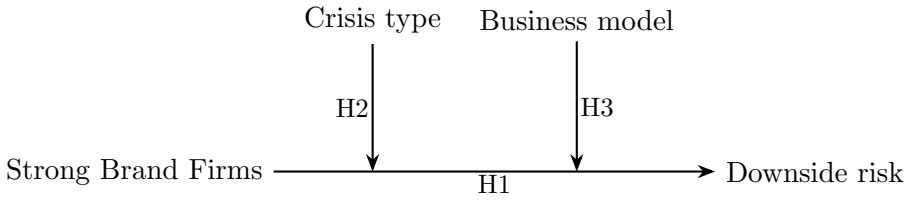
The proposed hypotheses can be matched into two closely related but methodologically distinct relationship frameworks. These guide us through our empirical section:

Figure 5: First relationship (portfolio-level) discussed in this paper



Within the discussed portfolio-level relationships we treat the strong brand portfolio as independent variable (IV), downside risk as dependent variable (DV) and crisis type as moderating variable.

Figure 6: Second relationship (firm-level) discussed in this paper



Within the discussed firm-level relationships we treat strong brand firms as independent variable (IV), downside risk as dependent variable (DV) and crisis type and business model as moderating variable and our industry classifications as control.

The first relationship framework (Figure 5) focuses on the link between the Strong Brands Portfolio (SBP) and downside risk. As we treat brand equity as a core strategic asset that might be able to explain variation in downside risk, we see SBP as an appropriate explanatory variable. We begin by examining the full sample period to assess whether strong brands are associated with lower downside risk. If brand equity exhibits resilience, we expect the strong brand portfolio to exhibit weaker sensitivity to negative market movements and smaller losses in bad states. Crisis periods play a central role in shaping how firms behave in adverse markets and they may meaningfully alter the

relationship between brand equity and downside risk. We therefore then add to H1 and test whether crises have a moderating effect, such that the behaviour of portfolios differs in crisis periods compared with downside months outside the defined crisis periods.

The second relationship framework (Figure 6) examines Strong Brand Firms (SBF) at the firm-level. The SBF variable mirrors the logic behind SBP but instead classifies strong brands at the firm-level rather than on the portfolio-level. This allows us to study whether the relationship between brand equity and downside risk is similar at the firm-level. On the firm-level, we also implement industry fixed effects to mitigate concerns that industry-specific risk exposure, sectoral cyclicality or technological intensity could bias the estimated coefficients. We first test H1 and H2 again, but now at the firm-level. The aim here is to establish if the relationship is the same once firm-level heterogeneity is taken into account. Furthermore, we show whether another moderator influences the relationship significantly. In order to do this, we first test the association between business model and industry. We expect the relation to be strong and thus proceed by focusing on business model as another moderator and include our industry classifications as controls to avoid multicollinearity.

Our approach relies on understanding what generates variation in brand equity and downside risk. This means ensuring that this variation is not driven by unobserved factors. The key identifying variation in both SBP and SBF is generated by Interbrand's ranking methodology (A.3). The structural differences embedded in this methodology determine which firms appear in the rankings and therefore generate the β_1 in both relationship frameworks.

At the same time, downside risk is influenced by several factors unrelated to brand equity. We believe that these include industry cyclicality, financial structure, macroeconomic sensitivities and idiosyncratic firm events. These elements form the economic content of the error term in both portfolio- and firm-level regressions. To mitigate omitted-variable concerns, we incorporate standard asset-pricing controls. Both downside beta and downside excess returns are estimated using the Fama-French six-factor model. At the firm-level, industry fixed effects further absorb sector-specific risk exposure and technological intensity, while crisis dummies isolate the influence of major macroeconomic episodes. These controls make it more plausible that unobserved downside risk factors are not systematically correlated with brand equity.

Thereafter, we conduct several robustness tests to verify that our empirical results are not driven by model choices or classification decisions. We re-estimate our baseline and crisis models using alternative full-year crisis definitions to see whether our baseline definitions overlook any effects. Also, we test if our results hold when removing the assumption of holding the Interbrand rankings from 2000 steady for 1998 and 1999. As a final robustness check, we conduct a further analysis based on an alternative measure of brand equity introduced by Boustanifar and Kang (2025). We construct new strong brand portfolios, both value-weighted and equal-weighted, based on the firms that appear most frequently in their annual filings[3] when the words "brand" or similar terms are normalised per 10,000 words. Figure 8 shows an example value-weighted portfolio for 2024. Each year, we select the top 100 firms according to this text-based measure and form updated portfolios following the same annual rebalancing schedule as in our main specification. We run the same type of analyses as with the Interbrand data and compare the results to assess consistent results.

3. The appendix outlines the construction and methodology of the alternative brand measure (A.6.1)

4 Empirical analysis

4.1 Is There a Brand Premium over a Long Period of Time?

First, we replicate the key finding of Boustanifar and Kang (2025) using the same methodology, but extending the sample to 2024.

Table 4: Estimation of monthly excess returns for the Interbrand equal- and value-weighted portfolios

	EW-Portfolio	VW-Portfolio
Const.	0.0019**	0.0055***
	(0.0008)	(0.0009)
MKT	1.0023***	0.9963***
	(0.0298)	(0.0353)
SMB	-0.0096	-0.1902***
	(0.0413)	(0.0439)
HML	0.0106	-0.1768***
	(0.0364)	(0.0503)
RMW	0.0450	0.0470
	(0.0497)	(0.0454)
CMA	0.0515	-0.0677
	(0.0488)	(0.0617)
UMD	-0.1743***	-0.1301***
	(0.0395)	(0.0379)
R^2	0.9297	0.9156
Adj. R^2	0.9282	0.9138
N	290	290

Table 4 reports the results of estimating the monthly excess returns of the Interbrand-based equal- and value-weighted portfolios using the Fama-French six-factor model. The momentum factor is denoted as UMD (often referred to as MOM). The underlying regression specification is $ER_t = \alpha + \sum_k \beta_k \cdot Factor_{k,t} + \varepsilon_t$. The constant term in the output corresponds to the monthly intercept (alpha). The regression covers all months between November 2000 and the end of 2024. Standard errors are reported in parentheses. EW = Equal-weighted. VW = Value-weighted. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We find the intercept of the regression, that is, the abnormal return associated with firms that possess strong brands, to be positive and statistically significant. This so-called brand premium holds for both the equal-weighted and value-weighted portfolio. For the equal-weighted portfolio, the intercept implies an annual abnormal return of about 2.3%, while the value-weighted portfolio yields roughly 6.6%. Therefore, we find support for the findings using our data but do establish that the annual abnormal return we find for the value-weighted portfolio to be higher than what Boustanifar and Kang (2025) find. We explain the higher value-weighted coefficient with the exceptional performance of the largest strong brand firms in recent years, such as Apple or Nvidia.

4.2 Relationship Between Brand Equity and Downside Risk in Downside Markets

Table 5: Portfolio-level regression results of the relationship between brand equity and the three measures of downside risk

	Downside beta		**Downside excess returns**		**Semi-variance**	
	VW	EW	VW	EW	VW	EW
SBP	0.210*	-0.058	-0.006**	0.006**	0.000142	-0.000676***
	(0.126)	(0.129)	(0.002)	(0.003)	(0.000087)	(0.000199)
MKT			0.956***	1.057***		
			(0.027)	(0.035)		
SMB			-0.028	0.410***		
			(0.028)	(0.041)		
HML			-0.042	-0.019		
			(0.034)	(0.040)		
RMW			0.054	-0.054		
			(0.035)	(0.046)		
CMA			0.073	0.089		
			(0.049)	(0.070)		
UMD			-0.017	-0.073***		
			(0.019)	(0.028)		
Observations	584	584	232	232	232	232

Table 5 reports time-series regressions of the three monthly portfolio downside risk measures on brand equity. The dependent variable is the downside beta, downside excess return or semi-variance. A dummy variable equals 1 for the strong brand portfolio and 0 for the weak brand portfolio. The coefficient on this dummy, β_1, measures the difference in downside beta between the strong brand and the weak brand portfolios. For each downside risk measure, we show both value-weighted and equal-weighted results as well as the monthly observations. OLS estimates use Newey-West heteroskedasticity- and autocorrelation-robust standard errors. SBP = Strong brand portfolio. VW = Value-weighted portfolio. EW = Equal-weighted portfolio. Specifications with downside excess return additionally incorporate the Fama-French six factors to control for common sources of systematic risk. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We show the regression results of downside risk on brand equity for the three introduced measures of downside risk in Table 5. We find that when calculating downside risk with downside beta, the coefficient for value-weighted portfolios is positive and significant. This indicates that value-weighted portfolios exhibit increased downside risk for this measure of risk. This hints towards large-cap strong brand firms being more volatile than the market during months in which the market is negative. However, the coefficient for equal-weighted portfolios for the same risk measure is negative and insignificant. This gives only directional context and indicates descriptively that smaller, strong brand firms may be marginally less exposed to downside risk. We acknowledge that any conclusions from this cannot be drawn, but the other downside risk measures give us a better picture

here. Either way, for downside beta, we can only reject the null hypothesis for the value-weighted portfolio.

We find the same directional pattern with gained significance considering downside excess returns for both types of portfolio weighting. Value-weighted strong brand portfolios earn roughly 0.6 percentage points lower monthly excess return compared to weak brand value-weighted portfolios. This supports our downside beta findings, as value-weighted strong brand portfolios can now be associated with increased downside risk for both risk measures. Similarly, the equal-weighted portfolio complements the finding of downside beta with significant results. The strong brand coefficient is positive and significant. This indicates that in downside market months, the average strong brand stock tends to exhibit higher downside excess returns than the average weak brand stock. We can therefore reject the null hypothesis for both weighting schemes of portfolios. The relative findings are best understood as differences in how strong and weak brand firms behave during downturns. From an investor perspective, this outperformance in the equal-weighted portfolio is economically meaningful. Practically, this means that the equal-weighted portfolio can be associated with smaller realized losses during downside markets. The factor loadings behave as expected. The market factor is significant, reflecting that downside portfolio returns move strongly with the market in bad months. In the equal-weighted regression, the SMB factor is also positive and significant. This shows that small-cap exposure is more important for average strong brand stocks. Additionally, UMD becomes significant in the equal-weighted regression, suggesting that momentum effects are more pronounced among smaller firms when all firms contribute equally to the portfolio.

For semi-variance, we observe the same directional pattern as for the other two measures. For the value-weighted portfolio, we see that the negative tail of the return distribution is wider for larger strong brand firms, although its insignificance again means that our conclusion cannot be made. For the equal-weighted portfolio, it is now significant and therefore can be associated with lower downside dispersion.

The firm-level analysis (Table 14) reveals results consistent with the equal-weighted portfolio patterns across all three downside risk measures. Importantly, the firm-level regressions yield statistically significant coefficients for downside beta. This now allows us to reject the null hypothesis for all three measures of downside risk. Furthermore, all measures indicate that strong brands are associated with lower risk in downside markets. We also observe that the magnitude of the coefficients is generally larger at the firm-level, suggesting that the impact of brand equity on downside risk is stronger when heterogeneity across firms is accounted for. The control variables, which include Fama-French 6 and industry sectors, are all significant. This suggests that our relationship reflects a distinct pattern in the data, rather than being solely attributable to omitted industry effect or standard risk exposure.

4.3 The Moderating Role of Crisis Periods in the Brand Equity-Downside Risk Relationship

Table 6: Portfolio-level regression results of the relationship between brand equity and the three measures of downside risk moderated by crisis

	Downside beta		**Downside excess returns**		**Semi-variance**	
	VW	EW	VW	EW	VW	EW
SBP	0.101	-0.034	-0.002	0.003	0.000145***	-0.000767***
	(0.149)	(0.166)	(0.002)	(0.004)	(0.000040)	(0.000241)
DotCom	-0.120	0.302*	0.012***	0.005	0.000484**	-0.000074
	(0.193)	(0.158)	(0.003)	(0.006)	(0.000193)	(0.000253)
GFC	-0.026	-0.194	0.007***	-0.004	0.000162***	-0.000024
	(0.109)	(0.206)	(0.002)	(0.004)	(0.000056)	(0.000390)
COVID	0.251***	0.441***	-0.007**	-0.013	-0.000033	0.002066**
	(0.082)	(0.131)	(0.003)	(0.009)	(0.000033)	(0.000941)
Energy shock	0.061	0.854*	0.008***	-0.007	0.000161***	-0.000256
	(0.134)	(0.496)	(0.002)	(0.005)	(0.000048)	(0.000241)
SBP × DotCom	0.575	-0.126	-0.018***	0.013	-0.000251**	0.000495*
	(0.415)	(0.213)	(0.006)	(0.010)	(0.000114)	(0.000271)
SBP × GFC	0.541*	0.092	-0.002	0.002	0.000182	0.000323
	(0.309)	(0.265)	(0.004)	(0.005)	(0.000119)	(0.000392)
SBP × COVID	-0.055	-0.290	0.033***	0.034***	0.001300***	-0.002134**
	(0.153)	(0.183)	(0.004)	(0.010)	(0.000239)	(0.000946)
SBP × Energy shock	0.146	-0.243	-0.019***	0.000	-0.000173***	0.000370
	(0.209)	(0.351)	(0.005)	(0.007)	(0.000057)	(0.000241)
MKT			0.977***	1.049***		
			(0.017)	(0.028)		
SMB			-0.034	0.388***		
			(0.028)	(0.032)		
HML			-0.022	-0.007		
			(0.034)	(0.042)		
RMW			0.030	-0.147***		
			(0.037)	(0.048)		
CMA			0.059	0.052		
			(0.051)	(0.055)		
UMD			-0.021	-0.079***		
			(0.016)	(0.020)		
Observations	584	584	232	232	232	232

Table 6 reports time-series OLS regressions of monthly downside beta, downside excess return and semi-variance on a strong brand indicator, crisis-period dummies and their interactions. Crisis indicators

(*DotCom*, *GFC*, *COVID*, *ES*) equal 1 within their respective windows and 0 otherwise. Interaction terms (*SBP* $\times$ *Crisis*) capture the incremental effect for strong brand portfolios during crises. The baseline coefficient captures the effect of strong brands in downside markets outside of crisis definitions. Newey-West standard errors are reported in parentheses. SBP = Strong brand portfolio. VW= Value-weighted portfolio. EW = Equal-weighted portfolio. ES = Energy shock. Specifications with downside excess return additionally incorporate the Fama-French six factors to control for common sources of systematic risk. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6 adds on by now including crisis as a moderator to the relationship between brand equity and downside risk. We interpret the coefficient on the strong brand indicator as capturing the behavior of the strong brand portfolio in all downside months outside the crisis windows. These non-crisis months serve as the benchmark and function as the omitted category in the regression. In both the value-weighted and equal-weighted specifications, this coefficient moves in the same direction as in the baseline relationship for all measures of downside risk. Semi-variance is the only risk measure that yields a statistically significant coefficient for the strong brand portfolio. This result indicates that, during non-crisis downside markets, a value-weighted portfolio of strong brands is associated with higher risk. In contrast, an equal-weighted portfolio of strong brands is associated with lower risk for semi-variance. The other measures of downside risk are insignificant and thus we can only interpret their directions.

For downside beta, we get mixed results when we look at crisis interactions. We have one positive and significant interaction term for the value-weighted portfolio under GFC. Therefore, we can reject the null hypothesis and say that crisis moderates the relationship between brand equity and downside beta. The other interaction terms for value-weighted and equal-weighted portfolios are insignificant and point into different directions. We can interpret the positive and significant interaction term of the Global Financial Crisis with the findings of Claessens and Kose (2013). They show that credit-driven crises create liquidity stress and funding problems that overshadow firm-specific strengths. In such situations, investors may pay less attention to long-term intangible assets, which helps explain why the GFC shows a different association between brand equity and downside sensitivity than the other crises. Our findings for the equal-weighted portfolio using downside beta show that crisis periods do not systematically change how brand equity relates to downside beta for an average firm. We therefore fail to reject the null hypothesis for the equal-weighted portfolio.

For downside excess returns, we observe a similar mixed pattern regarding the crisis interaction terms. We find that the number of significant interaction terms has increased. However, we do not see any significance for the Global Financial Crisis interaction term. We instead find significance for COVID, the Energy Shock and the DotCom crisis. Importantly, we must interpret our COVID results carefully as we define COVID to span only four months. Therefore, the precision of results is limited, and the economic meaning must be interpreted carefully. Even so, the direction of the COVID interaction term aligns with the pattern observed in the downside beta regressions. For the other crisis interaction terms, we cannot make the same comparison with downside beta. We observe variation in both the signs and the significance levels of the interaction terms, especially across the different weighting schemes. Nonetheless, we observe more significant terms in the value-weighted portfolios, indicating that crisis-specific variation is more pronounced for larger, strong brand firms than for the average firm represented in the equal-weighted portfolio. In general, since at least one crisis interaction term is statistically significant in

both weighting schemes, we reject the null hypothesis for both portfolio types when using downside excess return as our downside risk.

The mixed evidence remains apparent when considering semi-variance. The same crisis can be associated with either higher or lower downside risk, depending on the portfolio's weighting scheme, an example is the COVID interaction term. This example provides further evidence that crisis-specific associations likely reflect distinct mechanisms underlying each shock and how they align with the composition of the strong brand portfolios. Regardless, we reject the null hypothesis for both the value- and equal-weighted portfolios.

When analyzing the relationship between brand equity and downside risk at the firm-level (Table 15), we find results that are consistent across the three downside risk measures with the patterns observed in the equal-weighted portfolio. Importantly, the firm-level regressions also yield statistically significant coefficients for downside beta and downside excess returns for the baseline coefficients. This now allows us to reject the null hypothesis for all three measures of downside risk. We observe stronger, more consistent and more frequently significant crisis interactions on the firm-level. This suggests that crisis-specific mechanisms influencing the association between brand equity and downside exposure are harder to detect in aggregated portfolios but become more apparent when individual firm differences are taken into account. The control variables behave as expected.

4.4 Association Between Business Model and Industry Groups

Figure 7: Normalized distribution of business models by industry

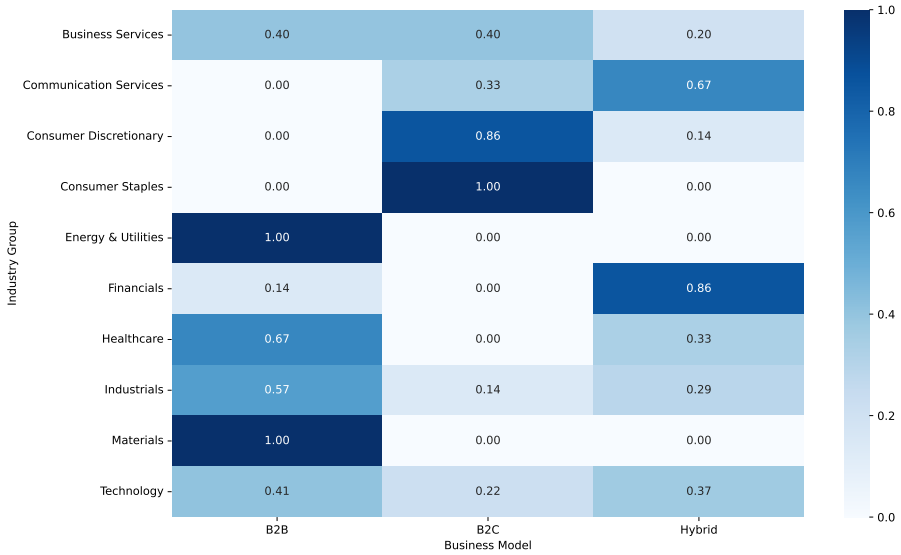


Figure 7 visualizes the distribution of business models across industries using a row-normalized contingency table. Each strong brand firm is assigned their dominant business model and industry group. For each industry group, the proportion of firms belonging to each business-model category are displayed. Darker cells indicate a higher concentration of firms with a given business model within that industry. As the spectrum for what falls under Business Services is quite wide, we get associations that might be unintuitive initially. For instance, Disney and eBay both fall under the business services industry, yet clearly have different customer bases compared to more traditional B2B-focused business service firms such as Accenture.

As both business models and industries can explain similar patterns in customer behavior, we expect them to be strongly associated. We calculate Cramér's V to evaluate any association and obtain a score of 0.6114. This implies that there is a strong association between business model and industry and that business model cannot be interpreted independently from industry. Consequently, when using business models as a moderator, we must include industry fixed effects to avoid omitted-variable bias. Also, we cannot treat both variables as mediators, as doing so would yield misleading or unstable results due to their overlap.

To illustrate this association, we also provide a heatmap overview (Figure 7). Additionally, let us consider a few examples. The consumer-staples industry consists almost entirely of consumer-facing firms, which is intuitive because products such as Pampers are directed toward end users. In contrast, the technology sector contains firms with very different customer orientations. Dell follows a hybrid model, Amazon operates mainly as a B2C firm, and Xerox is predominantly B2B. Elaborated guiding examples of business model classifications can be found in Appendix A.4. These examples show that although industry and business models are related, the strength of the association varies across sectors. This supports our use of the business model as the moderating variable and industry as a control. We treat business model as a moderator because it may alter our key relationship, while industry is included as a control since it is not central to our mechanism.

4.5 The Moderating Role of Business Model in the Brand Equity-Downside Risk Relationship

Table 7: Firm-level regression results of the relationship between brand equity and the three measures of downside risk moderated by business model

	Downside beta	*Downside excess returns*	*Semi-variance*
SBF	-0.226***(0.080)	0.016***(0.003)	-0.023***(0.004)
SBF × B2B	-0.118 (0.134)	-0.007 (0.005)	-0.017***(0.005)
SBF × Hybrid	0.589***(0.168)	-0.040***(0.006)	0.013***(0.004)
B2B	0.774***(0.032)	-0.007***(0.001)	0.033***(0.006)
Hybrid	0.449***(0.051)	0.001 (0.002)	0.012***(0.005)
Communication Services	1.190***(0.095)	0.007**(0.003)	0.026***(0.003)
Consumer Discretionary	1.267***(0.042)	0.008***(0.001)	0.034***(0.008)
Consumer Staples	0.227 (0.235)	0.016**(0.007)	0.018*(0.010)
Energy & Utilities	0.345***(0.063)	0.014***(0.002)	-0.004 (0.006)
Financials	0.488***(0.054)	0.023***(0.002)	0.004 (0.005)
Healthcare	1.236***(0.072)	0.012***(0.002)	0.035***(0.002)
Industrials	0.712***(0.030)	0.008***(0.001)	0.013***(0.005)
Technology	1.499***(0.032)	-0.016***(0.001)	0.042***(0.001)
MKT		1.053***(0.009)	
SMB		0.800***(0.011)	
HML		-0.092***(0.012)	
RMW		-0.238***(0.014)	
CMA		0.245***(0.016)	
UMD		-0.072***(0.007)	
Observations	1,149,060	536,883	536,883

Table 7 reports firm-level regressions of monthly downside beta, downside excess return and semi-variance on brand equity, business-model indicators, and their interactions. Business models are captured through *B2B* and *Hybrid* indicators, with *B2C* as the omitted category. Interaction terms (*SBF × B2B* and *SBF × Hybrid*) show how the association between brand equity and downside risk varies across business models. Industry fixed effects are included, and Fama-French six factors are added when downside excess return is the dependent variable. Standard errors are clustered at the firm-level. SBF = strong brand firm. Specifications with downside excess return additionally incorporate the Fama-French six factors to control for common sources of systematic risk. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In Table 7, we observe that B2B firms tend to have higher downside beta. The coefficient on the B2B dummy is positive and highly significant, indicating that business-facing firms exhibit greater downside sensitivity than B2C firms regardless of brands. The interaction term between strong brands and B2B firms is negative, although not significant. The main strong brand coefficient is negative but significant. Since the interaction term for B2B firms is insignificant, the moderation of a B2B business model is statistically insignificant in our relationship. However, without considering the interacting term, we see that having a strong B2B brand firm is associated with lower risk than a weak B2B brand firm. Despite this, having a B2B strategy is inherently riskier than a B2C strategy relative to our relationship.

For hybrid firms, the pattern differs. The hybrid dummy is positive and significant,

and the interaction between strong brands and hybrid firms is also positive and significant. This indicates that hybrid firms tend to have higher downside beta, and that strong brand status is associated with even greater downside sensitivity within this group. This holds even when adding the main strong brand coefficient. Hybrid firms therefore appear to exhibit the highest downside exposure in this measure of risk. A possible explanation is explained by Markides and Charitou (2004). They argue that dual business models can create internal tension and strategic misalignment when firms rely on different customer logics or operating processes. Their work shows that managing two models within the same organisation is often associated with conflicting priorities, inconsistent resource allocation and difficulty sustaining a clear strategic direction.

B2C firms act as the omitted variable category in our model. The strong brand coefficient reflects the association between brand equity and downside beta within B2C firms. This coefficient is negative and significant, indicating that strong brand B2C firms tend to exhibit lower downside beta than weak brand B2C firms. This pattern suggests that brand equity is associated with greater downside stability for consumer-facing firms.

The significant interaction term of hybrid for downside beta allows us to reject the null hypothesis. We find that business model moderates the relationship between brand equity and downside risk in a meaningful way.

For the other risk measures, the baseline coefficient for strong brand B2C firms follows the same significant and directional pattern. For downside excess return, having a strong B2B firm is able to offset the risk of having a business-facing strategy, which was not possible for downside beta. This is because we are now able to significantly incorporate our moderating effect into our total effect of having a B2B strategy. Moving on to hybrid, we see a similar result as in downside beta, although with a different reasoning. Having a weak brand hybrid firm is associated with a lower risk than having a strong brand hybrid firm. Inherently, a weak hybrid model does not have a different downside risk than following a B2C strategy since the coefficient is insignificant. Regarding the hypothesis testing, we observe the same results as under downside beta.

Having a B2B when using semi-variance as a risk measure, we see the same direction as the downside beta. However, now we observe significant results for the baseline, the B2B coefficient and the B2B interaction term. Together, we associate strong brand B2B firms with a lower downside risk than weak brand B2B firms. Inherently, having a weak brand B2B firms is associated with a higher downside risk, while we can observe that strong brand B2B firms exhibit lower downside risk. Furthermore, we observe the same effects of having a hybrid strategy as in the downside beta case. Lastly, for semi-variance, we are able to reject the null hypothesis.

4.6 Robustness Tests

4.6.1 Alternative Crisis Definition

Table 8: Portfolio-level regression results of the relationship between brand equity and the three measures of downside risk moderated by crisis (alternative definition)

	Downside beta		**Downside excess returns**		**Semi-variance**	
	VW	EW	VW	EW	VW	EW
SBP	-0.002	-0.088	0.001	0.007**	0.000181***	-0.000489***
	(0.152)	(0.157)	(0.002)	(0.003)	(0.000044)	(0.000094)
DotCom	-0.053	0.330**	0.015***	0.013**	0.000540***	0.000593
	(0.169)	(0.134)	(0.003)	(0.005)	(0.000199)	(0.000405)
GFC	0.033	-0.318*	0.006***	0.001	0.000150***	0.000180
	(0.110)	(0.191)	(0.002)	(0.003)	(0.000053)	(0.000320)
COVID	0.122	0.337***	0.002	-0.001	0.000123***	0.001379***
	(0.093)	(0.123)	(0.004)	(0.004)	(0.000038)	(0.000483)
Energy shock	-0.036	0.868**	0.012***	0.005	0.000266***	0.001110
	(0.168)	(0.394)	(0.002)	(0.006)	(0.000048)	(0.000962)
SBP × DotCom	0.601	-0.112	-0.022***	0.001	-0.000332**	-0.000204
	(0.387)	(0.192)	(0.005)	(0.005)	(0.000151)	(0.000422)
SBP × GFC	0.676***	0.569*	-0.004	-0.001	0.000144	0.000049
	(0.262)	(0.334)	(0.005)	(0.006)	(0.000097)	(0.000293)
SBP × COVID	0.240	-0.001	0.004	0.010	0.000677***	-0.001431***
	(0.160)	(0.195)	(0.009)	(0.007)	(0.000186)	(0.000485)
SBP × Energy shock	0.556	-0.355	-0.023***	-0.016*	-0.000293***	-0.000999
	(0.342)	(0.335)	(0.004)	(0.009)	(0.000066)	(0.000952)
MKT			0.972***	1.070***		
			(0.020)	(0.026)		
SMB			-0.042	0.372***		
			(0.028)	(0.031)		
HML			-0.035	-0.017		
			(0.040)	(0.036)		
RMW			0.030	-0.149***		
			(0.037)	(0.049)		
CMA			0.063	0.048		
			(0.047)	(0.047)		
UMD			-0.022	-0.087***		
			(0.016)	(0.021)		
Observations	584	584	232	232	232	232

Table 8 reports time-series OLS regressions of monthly downside beta, downside excess return and semi-variance on a strong brand indicator, crisis-period dummies and their interactions. Crisis indicators (*DotCom*, *GFC*, *COVID*, *Energy shock*) equal 1 within their respective windows and 0 otherwise. Interaction terms (*SBP* × *Crisis*) capture the incremental effect for strong brand portfolios during crises. The baseline coefficient captures the effect of strong brands in downside markets outside of crisis definitions. Newey-West standard errors are reported in parentheses. SBP = strong brand portfolio. VW= Value-weighted portfolio. EW = Equal-weighted portfolio. ES = Energy shock. Specifications with downside excess return additionally incorporate the Fama-French six factors to control for common sources of systematic risk. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Extending the crisis windows to full calendar years (Table 8) results in similar coefficients for downside market times outside the specified crises definitions regarding any significant results when compared to Table 6. We find similar significance and direction for semi-variance across both portfolios. Notably, extending to full years enables us to say that we can find that brand equity can be associated with higher downside excess returns for equal-weighted portfolios and therefore relatively lower downside risk.

For downside beta, we find all the crisis interaction terms to be positive, and for the Global Financial Crisis as well as the Energy Shock to be significant. Meaning that we are able to reject the null, but that crisis moderates the relationship in a way that increases risk. This broadly shows what we find earlier and supports the argument that under the value-weighted portfolio, brand equity may be associated with higher downside risk and that crises exhibit to strengthen this effect. As a difference for downside beta, we now find a significant crisis interaction term for the Global Financial Crisis in the equal-weighted portfolio. This extends the argument of Claessens and Kose (2013) even further. The impact of the Global Financial Crisis exerts an even stronger effect on the relationship between brand equity and downside risk, as the equal-weighted portfolio indicates that long-term intangible assets may have played a reduced role. This change suggests that the effect does not depend on the portfolio construction.

The crisis-moderation findings are generally robust when evaluated through downside excess returns. We do, however, find that the large and significant positive effects we find for COVID now are insignificant. We can attribute this to the widened crisis period, which includes calmer non-crisis months around the period of distress. The same holds if we look at semi-variance. Most terms remain unchanged and only change slightly in magnitude. Interestingly, the large and significant effect we find for COVID stays persistent under this measure. We can explain this with the underlying differences in method. Because downside excess returns capture the average loss on down days, they react strongly when the COVID window is shorter, and now when we include more recovery months with smaller or fewer negative returns. Semi-variance, however, is driven mainly by the extreme losses in March-April 2020, and since those remain in every crisis definition, its results barely change. This highlights the consistent pattern that different specifications, portfolio types and downside risk measures do give varying results and have to be considered together. Despite all the changes, we are able to reject the null for all measures of risk and all portfolio weightings, reassuring that crisis is moderating the relationship.

At the firm-level (Table 16), our results gain significance and for most crises interactions, we do find large effects that can be associated with crises moderating this relationship. A possible explanation for this is the improved crisis isolation effect we can get from considering the firm-level. On the portfolio-level, we receive a weighted average of many industries and firm types. Some strong brand industries (e.g., tech during COVID) actually benefited, while others did not, and the value weights shift these effects around.

This aggregation washes out the clean firm-level pattern, so the crisis interactions become mixed. When expanding crisis periods, these effects may be leveraged, and industries diverge even more in how they affect.

4.6.2 Control of Ranking Assumption

Table 9: Portfolio-level regression results of the relationship between brand equity and the three measures of downside risk (without the years 1998 and 1999)

	Downside beta		**Downside excess returns**		**Semi-variance**	
	VW	EW	VW	EW	VW	EW
SBP	0.177	-0.048	-0.005**	0.007**	0.000145**	-0.000601***
	(0.122)	(0.133)	(0.002)	(0.003)	(0.000059)	(0.000189)
MKT			0.945***	1.059***		
			(0.026)	(0.035)		
SMB			-0.031	0.411***		
			(0.030)	(0.046)		
HML			-0.028	-0.007		
			(0.034)	(0.044)		
RMW			0.048	-0.052		
			(0.030)	(0.049)		
CMA			0.048	0.056		
			(0.048)	(0.071)		
UMD			-0.010	-0.055*		
			(0.022)	(0.030)		
Observations	567	567	212	212	212	212

Table 9 reports time-series regressions of the three monthly portfolio downside risk measures on brand equity. The dependent variable is the downside beta, downside excess return or semi-variance. A dummy variable equals 1 for the strong brand portfolio and 0 for the weak brand portfolio. The coefficient on this dummy, β_1, measures the difference in downside beta between the strong brand and the weak brand portfolios. For each downside risk measure, we show both value-weighted and equal-weighted results as well as the monthly observations. OLS estimates use Newey-West heteroskedasticity- and autocorrelation-robust standard errors. SBP = strong brand portfolio. VW = Value-weighted portfolio. EW = Equal-weighted portfolio. Specifications with downside excess return additionally incorporate the Fama-French six factors to control for common sources of systematic risk. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

To evaluate whether our ranking assumption influences the results, we re-estimate the model after excluding 1998 and 1999 and applying the 2000 ranking retrospectively (Table 9). Overall, the results remain directionally consistent with the baseline (Table 5). This suggests that the assumption does not materially alter the underlying relationships. Downside excess returns are virtually unchanged in sign, magnitude and significance across both weighting schemes. This indicates that the return-based effect of strong brands is robust to the revised ranking. In contrast, downside beta shows weaker

results. The value-weighted portfolio loses statistical significance and the size of the effect becomes smaller. The equal-weighted portfolio also shows a smaller effect than in the original model, but the direction is unchanged. Overall, the weaker statistical evidence combined with smaller coefficients suggests that downside beta is more sensitive to the ranking adjustment. For semi-variance, removing the assumption produces stronger results in the value-weighted specification, with larger coefficients and higher significance than in the baseline, indicating an increase in downside risk when using this weighting scheme. Conversely, the equal-weighted estimate becomes smaller, reflecting lower downside risk relative to the original model. These results indicate that semi-variance is sensitive to portfolio weighting, with value-weighting amplifying risk in the revised sample, while equal-weighting dampens it. The firm-level results (Table 17) are highly consistent across both specifications, with the same sign and level of statistical significance for all downside risk measures. The only differences are small shifts in magnitude, which do not change the interpretation of the results.

Overall, this robustness test shows that our results are largely stable across portfolio weighting schemes. The ranking assumption does not change the direction or significance of most relationships. However, downside beta becomes weaker and semi-variance reacts to weighting choices. Firm-level results remain essentially unchanged.

4.6.3 An Alternative Approach Towards Measuring Brand Equity

Table 10: Portfolio-level regression results of the relationship between brand equity and the three measures of downside risk (alternative brand measure method)

	Downside beta		**Downside excess returns**		**Semi-variance**	
	VW	EW	VW	EW	VW	EW
SBP	-0.213	0.065	-0.007**	0.006**	0.001353**	0.000189
	(0.158)	(0.172)	(0.003)	(0.003)	(0.000663)	(0.000380)
MKT			0.911***	1.044***		
			(0.089)	(0.045)		
SMB			0.112	0.808***		
			(0.080)	(0.048)		
HML			0.058	-0.056		
			(0.088)	(0.062)		
RMW			-0.085	-0.094		
			(0.088)	(0.066)		
CMA			0.201*	0.212**		
			(0.118)	(0.101)		
UMD			0.019	-0.083*		
			(0.055)	(0.043)		
Observations	582	582	232	232	232	232

Table 10 reports time-series regressions of the three monthly portfolio downside risk measures on brand equity. The dependent variable is the downside beta, downside excess return or semi-variance. A dummy

variable equals 1 for the strong brand portfolio and 0 for the weak brand portfolio. The coefficient on this dummy, β_1, measures the difference in downside beta between the strong brand and the weak brand portfolios. For each downside risk measure, we show both value-weighted and equal-weighted results as well as the monthly observations. OLS estimates use Newey-West heteroskedasticity- and autocorrelation-robust standard errors. SBP = strong brand portfolio. VW = Value-weighted portfolio. EW = Equal-weighted portfolio. Specifications with downside excess return additionally incorporate the Fama-French six factors to control for common sources of systematic risk. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

When we replace the Interbrand measure with the alternative brand metric, several patterns change (Table 10). We observe that applying the alternative brand measure produces a different coefficient sign for both portfolios for downside beta, as compared to our baseline (Table 5). As the observations are insignificant, we cannot reject the null hypothesis. We can therefore here not say that the value-weighted strong brand portfolio can be associated with higher downside risk. Therefore, strong brands cannot reliably be associated with either higher or lower downside risk.

In contrast, the results for downside excess returns stay almost identical. Stronger brands continue to exhibit lower downside risk, and the coefficient is almost identical. The only difference is that the CMA factor is now significant for both portfolios regarding downside excess returns. This indicates that investment-related characteristics gain explanatory power when we apply the alternative brand measure method.

For semi-variance, we conclude similar as to downside beta as the pattern reverses, with the value-weighted portfolio now being significant and the equal-weighted portfolio being insignificant. Overall, this robustness check follows our established pattern that the relationship between brand equity and downside risk remains sensitive to the chosen downside measure and weighting scheme. The consistent result that the strong brand value weighted portfolio can be associated with higher downside risk does not find support in this robustness check under downside beta. However, we are now able to find support for semi-variance. When we compare on a firm-level (Table 18), we observe that downside beta and downside excess return lose their significance, meaning that they are sensitive to the method of measuring brand. The semi-variance, however, shows robust findings.

Overall, we do not find consistent results for either portfolio- and firm-level, which is consistent with the reasoning we get from Keller (2013), Lev and Gu (2016) and Shi et al. (2021). We support their research, as our evidence shows that brands pose inherent difficulties for measurement.

Table 11: Portfolio-level regression results of the relationship between brand equity and the downside risk measures moderated by crisis (alternative brand measure method)

	Downside beta		**Downside excess returns**		**Semi-variance**	
	VW	EW	VW	EW	VW	EW
SBP	-0.216	0.110	-0.006*	0.002	0.000670**	-0.000176
	(0.186)	(0.213)	(0.003)	(0.003)	(0.000262)	(0.000167)
DotCom	-0.120	0.302*	0.012	0.002	0.000484**	-0.000074
	(0.197)	(0.160)	(0.008)	(0.005)	(0.000193)	(0.000253)
GFC	-0.026	-0.194	0.006*	-0.005	0.000162***	-0.000024
	(0.109)	(0.206)	(0.003)	(0.004)	(0.000056)	(0.000390)
COVID	0.251***	0.441***	-0.006	-0.005	-0.000033	0.002066**
	(0.082)	(0.131)	(0.004)	(0.008)	(0.000033)	(0.000941)
Energy shock	0.061	0.854*	0.000	-0.011***	0.000161***	-0.000256
	(0.134)	(0.496)	(0.005)	(0.004)	(0.000048)	(0.000241)
SBP × DotCom	-0.254	-0.258	0.001	0.017*	0.003927***	0.002037***
	(0.316)	(0.245)	(0.011)	(0.009)	(0.001338)	(0.000487)
SBP × GFC	0.060	0.576	-0.019**	0.008*	0.000496	0.000177
	(0.584)	(0.408)	(0.008)	(0.005)	(0.000342)	(0.000384)
SBP × COVID	0.186	-0.607***	0.001	-0.019***	-0.000384	0.000376
	(0.187)	(0.227)	(0.005)	(0.006)	(0.000266)	(0.000738)
SBP × Energy shock	0.293	-0.778*	0.007	0.013*	-0.000022	0.000031
	(0.422)	(0.434)	(0.004)	(0.007)	(0.000342)	(0.000211)
MKT			0.914***	1.034***		
			(0.090)	(0.043)		
SMB			0.084	0.769***		
			(0.077)	(0.040)		
HML			0.034	-0.069		
			(0.111)	(0.055)		
RMW			-0.165	-0.192*		
			(0.142)	(0.104)		
CMA			0.156	0.192*		
			(0.101)	(0.103)		
UMD			0.009	-0.086***		
			(0.046)	(0.033)		
Observations	582	582	232	232	232	232

Table 11 reports monthly time-series OLS regressions of downside beta, downside excess return and semi-variance on strong brand, crisis-period dummies and their interactions. Crisis indicators (*DotCom*, *GFC*, *COVID*, *Energy shock*) equal 1 within their respective windows and 0 otherwise. Interaction terms (*SBP × Crisis*) capture the incremental effect for strong brand portfolios during crises. The baseline coefficient captures the strong brand effect in noncrisis downside markets. Newey-West standard errors are reported in parentheses. SBP = Strong brand portfolio. VW = Value-weighted portfolio. EW = Equal-weighted portfolio. Specifications with downside excess return additionally incorporate controls. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

When applying the alternative brand measure and comparing Table 6 and 11, the SBP coefficient changes sign in both value-weighted and equal-weighted portfolios for downside beta, and both estimates become statistically insignificant. The dummy variables remain broadly unchanged, which indicates that the baseline crisis effects are not affected by how brands are measured. The interaction terms change more noticeably. The GFC interaction loses significance and the value-weighted portfolio contains no significant interactions at all. In contrast, the equal-weighted portfolio shows significant interaction effects for COVID and the energy shock. This likely reflects differences in which firms are included in the alternative method portfolio. Overall, we can only reject the null hypothesis for the equal-weighted portfolio, which is the opposite pattern compared to the original results.

For downside excess returns, the SBP coefficient becomes statistically significant in the value-weighted portfolio, which points to higher downside risk for strong brands. The crisis dummies show changes in both significance and magnitude, which indicates that this measure is more sensitive to alternative brand definitions than downside beta. The interaction effects also change in terms of magnitude and significance, but we are still able to reject the null hypothesis for both portfolios. This differs from downside beta, where significance was lost for value-weighted portfolios.

Under the alternative brand measure, the equal-weighted portfolio loses significance for the SBP coefficient, while the value-weighted portfolio shows a stronger positive effect, indicating higher downside risk for strong brands. The crisis dummies remain largely unchanged, which mirrors the pattern observed for downside beta but differs from downside excess returns, where more variation occurred. Both portfolios lose some significance in the interaction effects, with only the GFC interaction remaining significant. Despite this reduction in significance, we are still able to reject the null hypothesis for both weighting schemes.

We are still able to reject the null for both portfolios when using downside excess returns and semi-variance, while downside beta shows a shift in statistical support. This suggests that downside beta is more sensitive to the alternative brand measure. Nonetheless, the overall pattern of results remains similar, which indicates that our main findings are not driven by the specific brand measure used. For the firm-level (Table 19), SBF shows similar patterns as the portfolio-level, where both downside beta and downside excess return lose significance. For the interaction terms, we lose and gain some significance. However, our null hypothesis is still rejected, meaning that crisis has a moderating effect on our relationships. The overall results are stable even when applying an alternative brand measure.

5 Discussion and Conclusion

Our findings reveal that brand equity's relationship with downside risk is conditional rather than universal. This challenges the conventional view of strong brands as uniformly defensive assets. For the average firm, reflected in equal-weighted portfolios and firm-level regressions, we find that strong brands tend to face lower downside risk across most measures. This pattern likely stems from customer loyalty, pricing power and reduced information asymmetry, providing cash flow stability during downside markets. However, this risk-minimization effect weakens or reverses for large-cap firms in value-weighted portfolios. Here, strong brand portfolios exhibit higher downside beta and lower

excess returns. A plausible explanation for this is that larger firms are more exposed to institutional rebalancing and liquidity pressures in crises. This might outweigh any fundamental brand advantages. In parallel, we observe heterogeneous effects across different crisis types and varying impact on the relationship between downside risk and brand equity. Given that crises emerge from different underlying mechanisms, this makes sense as their effects are unlikely to be uniform across firms. Alongside this, our business model analysis reveals that the business model affects the relationship between downside risk and brand equity. B2B firms with strong brands tend to remain inherently riskier than B2C firms during downside markets, even after controlling for brand equity. We apprehend that the mechanism through which brands provide some sort of downside protection operates differently in business-to-business contexts where purchasing decisions are driven by rational cost analyses and contract structures rather than consumer sentiment. These findings indicate that brand equity is an asset whose risk-mitigating properties depend on weighting schemes, market context and the nature of customer relationships.

A potential rationale for why strong B2B brands might be inherently riskier than strong B2C brands, based on our interpretation, is that B2B firms appear more exposed to customer concentration. We understand this structure as creating a situation in which revenues are highly dependent on a limited set of buyers, which could, in theory, amplify vulnerability to idiosyncratic shocks such as client loss or contract renegotiation. Furthermore, we interpret purchasing behavior in B2B markets as more rational, which offers less scope for the kind of emotional brand attachment that may help stabilize demand in consumer markets. From this perspective, the value of brand equity in B2B contexts seems more contingent on performance-based assessments and cost-benefit calculations, which could be especially exposed during periods of economic stress or organizational change.

A possible way to understand why different crises affect firms and brands differently is to assume that each crisis is driven by distinct mechanisms that translate into different types of pressures on firms. For example, the DotCom crash can be interpreted as a crisis rooted in valuation dynamics and sector-specific speculation. This may have made firms connected to technology and high-growth sectors particularly sensitive to rapid changes in market sentiment. By contrast, the Global Financial Crisis appears to have been driven by credit shortages and liquidity constraints, which we assume could have disproportionately affected firms that rely on external financing or that operate in environments where access to credit is crucial for day-to-day operations. Energy-related crises, on the other hand, seem to be linked to commodity price shocks and regional dependencies. This potentially exposes firms located in or dependent on energy-sensitive markets to cost volatility and supply uncertainty. Under this interpretation, the type of mechanism at play may determine which firms are more exposed to adverse outcomes during a crisis. Crises that suppress demand might be assumed to affect firms with more elastic demand or those dependent on discretionary spending. On the other hand, supply-side or financially driven crises might place greater strain on firms that face input cost variability or short-term funding requirements. In this sense, we interpret crisis effects as contingent on the underlying mechanism, with different crises likely impacting different sets of firms rather than exerting a uniform influence across the market.

Assessing the robustness of our findings, we see that the main patterns remain directionally consistent, although downside beta and semi-variance in value-weighted portfolios are sensitive to the Interbrand ranking assumption. Additionally, we find similar results

when using another output measure of brands, which means that we can associate value-weighted portfolios with higher risk, while equal-weighted portfolios are associated with lower risk. Importantly, this still depends on the measure of downside risk. For the crisis moderation, we can conclude that the results are consistent for downside excess return and semi-variance. However, for downside beta, we now observe that the equal-weighted portfolio exhibits crises as a moderating effect while the value-weighted portfolio does not. The different results shown by our alternative brand measure reinforce the difficulty of measuring brands.

Interpreting our findings in relation to existing theory highlights several nuances relative to prior research. In our analysis for downside excess returns, we show partly similar results compared to Boustanifar and Kang (2025). They document a strong brand premium in excess return averaged over longer periods, whereas we can now support this by finding that strong brands in equal-weighted portfolios have higher excess returns in downside markets. This is also the case for our downside excess return in our firm-analysis. However, our results contradict when it comes to the value-weighted portfolio. We cannot support value-weighted portfolios having higher excess returns in our analysis of downside periods. A possible explanation for coexistence of our finding with Boustanifar and Kang (2025) could be that value-weighted portfolios perform stronger in upside market periods, offsetting the underperformance during downside market turns. Another possible explanation could be the structure of the value-weighted portfolios, which concentrate weight on the largest firms in the market. These large-cap strong brand firms tend to move closely with aggregate market dynamics, and their returns exhibit a high degree of sensitivity to broad macro conditions. Further research, such as Rego et al. (2009), links brand equity to lower exposure to adverse conditions, but our results also indicate that such associations are not universal. Instead, the strength and direction of the statistical relationships vary across downside risk measures, crisis environments, firm size and business model context.

Moreover, looking at downside market periods separately deepens our understanding of brand equity by showing how it performs in both average and critical conditions. Our results for downside market beta offer further insight into the underlying mechanisms. By examining how strong brands co-move with the market, specifically during negative periods, we better understand whether brand equity provides resilience through reduced sensitivity to adverse market shocks. An interesting pattern emerges when comparing downside beta with realized downside performance. Although downside beta is the only measure that does not rely on a relative risk definition, it generally yields weaker statistical evidence for brand-related effects compared to the realized measures. This suggests that sensitivity to systematic downside movements does not align well with the channels highlighted in the theoretical literature, whereas downside excess returns and semi-variance reflect these channels more consistently.

Our crisis-related findings reinforce earlier research by showing that the impact of a crisis is not universal but depends on its underlying structural mechanisms. The firm-level analysis reveals a clearer and stronger effect, indicating that crisis dynamics operate primarily at the firm-level and that portfolio aggregation can mask meaningful heterogeneity. These results are consistent with the conclusions of Claessens and Kose (2013). They argue that crises differ in their fundamental features and therefore generate heterogeneous outcomes across firms. For example, when considering the downside measures, we observe that for the Energy Shock, we associate the crisis moderation as an increased risk

for value-weighted portfolios using downside excess return and for semi-variance value-weighted portfolios it is vice versa. Comparing within the downside beta measure, we observe that the GFC interaction term shows an increased risk for the value-weighted portfolio, but we cannot interpret the equal-weighted portfolio. At last, we observe that the firm-level shows that the DotCom crisis moderates across all three downside measures, while the portfolio analysis does not show a consistent moderating effect.

The business model results mirror distinctions emphasised in marketing research. Prior research documents systematic differences between B2C, B2B and hybrid contexts (Ulaga and Eggert, 2006; Lindgreen and Wynstra, 2005; Vargo and Lusch, 2004; Kowalkowski, Kindström, and Brehmer, 2011) and our estimates follow these broad patterns. Having a strong brand as a B2C company can be related to lower downside risk, consistent with the role that emotional attachment and customer-level loyalty play in consumer markets. In B2B settings, our results align with research emphasizing that value creation relies more on contractual relationships and service performance. Interestingly though, we would expect B2B brands to show lower downside risk, given the trust-based and relationship-driven nature of B2B markets (Ulaga and Eggert, 2006). While strong B2B brands do indeed have lower downside risk than weak B2B brands, B2B firms as a whole remain riskier than B2C firms. This suggests that core B2B market characteristics still shape downside risk, even when brand equity is taken into account. Considering a hybrid strategy, the mixed results we find are broadly compatible with the mentioned suggestion that mixed customer orientations may dilute brand-related effects.

These findings also have implications for investors and managers. For investors, the results indicate that strong brands should not be treated as a universal defensive characteristic. Downside resilience varies with firm size, crisis mechanism and business model, and large-cap strong brand firms often move closely with the market. This means that value-weighted brand-based portfolio tilts are unlikely to offer reliable downside protection. Firm-level fundamentals provide a more informative basis for evaluating downside exposure. Relative to downside beta, downside excess returns and semi-variance exhibit stronger empirical signals, particularly during crises when realized performance may be more relevant than systematic exposure.

For managers, the results show that brand building remains important, but its risk-related benefits are conditional. However, having a strong brand and following a B2C strategy can be associated with lower downside risk. Following a B2C strategy is also safer than incorporating a B2B or hybrid strategy in our context. The crisis-specific results also suggest that resilience varies by shock type, meaning that brand strategy should be aligned with the mechanisms most relevant to each firm's environment rather than assumed to operate uniformly across downturns.

We acknowledge several limitations in this study. First, brand equity is inherently difficult to measure and available metrics serve as proxies rather than complete representations of brand equity. Second, although the model diagnostics indicate violations of several OLS assumptions, we mitigate these through the use of HAC standard errors and robustness checks. Third, although WRDS and Interbrand are established and reliable data sources, they present practical challenges. The Interbrand dataset is not directly compatible with financial databases such as WRDS, requiring substantial manual matching of brands to firm identifiers, which is labour-intensive and potentially prone to human error. Constructing a consistent time series across multiple years also adds operational complexity that may affect sample size and coverage. These challenges do not undermine

the reliability of the data but highlight limitations related to accessibility, integration and measurement consistency. Finally, although our crisis windows and downside risk measures follow established research, they necessarily simplify complex events and cannot fully capture the organizational or market-level mechanisms influencing resilience.

These limitations point toward several avenues for future research. One direction is to test alternative crisis windows to determine whether brand resilience is most pronounced at the onset, peak or recovery phase of a shock. Another is to extend the analysis to non-US markets to examine how variation in regulation, consumer behavior or financial structure affects the brand-risk relationship. Finally, incorporating qualitative dimensions, such as leadership traits or strategic responses during downturns, could deepen the understanding of how brand equity interacts with broader organizational behavior in crisis contexts.

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A Appendix

A.1 AI Appendix

ChatGPT and Grammarly have been used for the formatting of tables in LaTeX, some coding-related tasks and as a grammar checker.

A.2 Model Diagnostics

Table 12: Model diagnostics for the portfolio-level regression of the three downside risk measures on brand equity (H1)

Model	DW	LB p(6)	LB p(12)	BP p	AD p	Max VIF
DB (VW)	2.45	< 0.001	< 0.001	0.013	< 0.001	n/a
DB (EW)	1.89	< 0.001	0.005	0.609	< 0.001	n/a
DER (VW)	2.53	0.004	0.032	0.006	< 0.001	2.50
DER (EW)	2.58	< 0.001	< 0.001	< 0.001	0.017	2.50
SV (VW)	1.66	< 0.001	< 0.001	0.165	< 0.001	n/a
SV (EW)	2.00	0.004	0.020	0.054	< 0.001	n/a

Table 12 reports diagnostic statistics for the portfolio-level regressions related to H1. DW = Durbin-Watson, LB = Ljung-Box, BP= The Breusch-Pagan test, AD = Anderson-Darling test and Max VIF = maximum variance inflation factor. p-values are reported for all tests. We perform these test on all downside risk measures and both weighting schemes. DB = Downside beta, DER = Downside excess return, SV = Semi-Variance, VW = Value-weighted and EW = Equal-weighted.

Table 12 reports a set of diagnostic tests for the portfolio-level regressions related to H1. The Durbin-Watson statistics suggest either no autocorrelation or only mild, therefore acceptable levels. However, the Ljung-Box tests show a consistent rejection of the null of uncorrelated residuals across downside risk measures and weighting schemes, indicating persistent serial dependence. The Breusch-Pagan test reveals heteroscedasticity in several models, most notably for downside beta in the equal-weighted specification. Importantly, heteroscedasticity does not imply that linear models are inappropriate per se. Rather, it indicates that the variance of the residuals changes with the predictor, which can arise when the relationship between variables differs by subgroup or context. In some cases, such patterns reflect a moderating effect, where a third variable interacts with the independent variable so that the effect size (beta) is not constant, but varies depending on the moderator.

The Anderson-Darling test uniformly rejects normality, which indicates non-normal residuals rather than normally distributed errors. However, given our large sample size, the central limit theorem mitigates the practical consequences. Lastly, all VIF values fall well below conventional thresholds, implying no issues with multicollinearity. Together, these results show that several OLS assumptions are violated, primarily concerning independence, homoscedasticity, and normality, which can affect the validity of standard errors. To address autocorrelation and heteroscedasticity, we use HAC standard errors, which provide robust inference under these conditions.

One of the core OLS assumptions is linearity. In practice, this requires a continuous relationship between predictors and the dependent variable. In our case, however, all predictors are dummy variables, which only take values 0 and 1, leading to inherently stepwise, rather than continuous, relationships. This makes traditional linearity diagnostics neither meaningful nor informative. While this could theoretically limit the interpretation of linearity in our models, we mitigate such concerns by applying alternative measures and definitions of downside risk as robustness checks, supporting the stability of our results.

Table 13: Model diagnostics for the portfolio-level regression of the three downside risk measures on brand equity moderated by crisis (H2)

Model	DW	LB p(6)	LB p(12)	BP p	AD p	Max VIF
DB×C (VW)	1.14	< 0.001	< 0.001	0.120	< 0.001	3.02
DB×C (EW)	1.77	0.003	< 0.001	0.008	< 0.001	3.02
DER×C (VW)	2.44	< 0.001	0.020	0.001	< 0.001	3.81
DER×C (EW)	2.66	< 0.001	< 0.001	< 0.001	0.192	3.81
SV×C (VW)	1.59	< 0.001	< 0.001	< 0.001	< 0.001	2.14
SV×C (EW)	1.90	0.250	0.590	0.058	< 0.001	2.14

Table 13 reports diagnostic statistics for the portfolio-level regressions related to H2. C denotes that this table considers the models including crisis as a moderator. DW = Durbin-Watson, LB = Ljung-Box, BP= The Breusch-Pagan test, AD = Anderson-Darling test and Max VIF = maximum variance inflation factor. p-values are reported for all tests. We perform these test on all downside risk measures and both weighting schemes. DB = Downside beta, DER = Downside excess return, SV = Semi-Variance, VW = Value-weighted and EW = Equal-weighted.

Table 13 reports diagnostic tests for the portfolio-level regressions related to H2. The Durbin-Watson statistics indicate either no or mild autocorrelation across most specifications, although some models show lower values that suggest more noticeable dependence. Consistent with this, the Ljung-Box tests generally reject the null of uncorrelated residuals, indicating persistent serial dependence across specifications, with only isolated exceptions. The Breusch-Pagan test again points to heteroscedasticity in several models, such as in one of the value-weighted specifications, suggesting time-varying volatility in the residuals.The Anderson-Darling test mostly rejects normality, indicating that residuals deviate from a normal distribution, which is typical for financial return data rather than a sign of model misspecification. Finally, VIF values remain below conventional cutoffs, suggesting that multicollinearity is not an issue.

Overall, these results imply violations of several OLS assumptions, which primarily affect the reliability of standard errors. As with the previous set of models, we use HAC standard errors to correct for autocorrelation and heteroscedasticity, ensuring valid inference under these conditions. Link back to methodology (3)

A.3 How Interbrand Does the Best Global Brands Rankings

Interbrand's methodology builds on a valuation framework that combines the financial performance of branded products and services, the extent to which the brand influences customer purchase decisions, and the overall strength of the brand, which reflects its ability to generate future earnings that can be attributed directly to the brand itself. Because this methodology is applied consistently across industries and is widely recognized in academic research, we treat Interbrand's rankings as a reliable output-based measure of brand equity and an appropriate proxy for identifying firms that possess strong and market-validated brands.

A.4 Guiding Examples of Business Model Classification

Consumer-facing: McDonald's

- **Primary customer/demand drivers:** Revenue almost entirely from individual consumers purchasing food and beverages, either directly or via franchisees
- **Brand communication:** Strong B2C focus - emotional and lifestyle branding ("I'm Lovin' It", "Feel-Good Moments"). Emphasizes convenience, affordability, and global accessibility
- **Industry definition**
  - NAICS 722513 - Limited-Service Restaurants
  - GICS 25301040 - Restaurants
  - both consumer-facing industries
- **Business mix:** Operates and franchises restaurants; franchise revenue structure adds a B2B element, but underlying demand remains consumer-driven
- **Relevant events that could change their focus:**
  - 2003 - Global brand overhaul with "I'm Lovin' It" → B2C reinforcing
  - 2015 - "Experience of the Future" initiative → digital B2C innovation
  - 2020 - Digital acceleration (McDelivery, loyalty app) → B2C reinforcing
  - 2023 - "Accelerating the Arches 2.0" strategy → continues B2C focus
- **Verdict: B2C across all periods**, franchise model adds minor B2B component structurally but not strategically

Business-facing: Deere & Company

- **Primary customer/demand drivers:**
  - Its primary customers are businesses and organizations, such as farms, agricultural enterprises, contractors, governments, and equipment dealers

- **Brand communication:**
  - "Nothing Runs Like a Deere." Marketing targets farmers, contractors, and institutional buyers, highlighting efficiency and technological advantages, not lifestyle or household consumption → enterprise-oriented communication
- **Industry definition**
  - NAICS 333111 - Iron and Steel Mills and Ferroalloy Manufacturing → B2B
  - GICS 20 - Industrials → B2B
- **Business mix:**
  - A global machinery and technology company providing integrated equipment and digital solutions for agriculture, construction, and forestry professionals
  - Main segments include: Production & Precision Agriculture, Small Agriculture & Turf, Construction & Forestry, Financial Services
  - Overall, the firm's operations are designed around organizational clients and professional use
- **Relevant events that could change their focus:** -
- **Verdict: Strong B2B**

Hybrid: MasterCard Incorporated

- **Primary customer/demand drivers:**
  - Its direct customers are banks, merchants, and financial service providers, who issue cards and process transactions via Mastercard's infrastructure
  - However, end-user activity by consumers (cardholders making payments) drives transaction volume and value
  - Hybrid, but structurally B2B-dominant due to organizational customers
- **Brand communication:**
  - Marketing and brand identity are consumer-facing - "Priceless" campaign, reinforcing trust and loyalty among end-users
  - However, strategic partnerships and sales efforts target banks, merchants, and fintech firms, consistent with a B2B service provider model
- **Industry definition**
  - NAICS: 522320 - Financial Transactions Processing, Reserve, and Clearinghouse Activities
  - GICS: 40 - Financials
- **Business mix:**

  - Mastercard earns revenue primarily from fees charged to issuers and acquirers, not consumers

- **Relevant events that could change their focus:**
  - 2006: Becomes a publicly traded company; expands partnerships with banks → B2B reinforcing
  - 2016-2020: Investments in fintech partnerships and digital wallets (Apple Pay, Google Pay) → B2C reinforcing
  - 2020-2022: COVID-19 accelerates digital payment adoption → increased consumer-driven demand
- **Verdict: Some B2B elements, but on the majority hybrid**

Link back to the heatmap (Figure 7)

A.5 Additional Firm-Level Empirical Tables

Table 14: Firm-level regression results of the relationship between brand equity and the three measures of downside risk

	Downside beta	*Downside excess return*	*Semi-variance*
SBF	-0.234***	0.008***	-0.029***
	(0.070)	(0.003)	(0.002)
Communication Services	1.190***	0.008***	0.026***
	(0.095)	(0.003)	(0.003)
Consumer Discretionary	1.290***	0.009***	0.034***
	(0.041)	(0.001)	(0.008)
Consumer Staples	0.677***	0.018***	0.029***
	(0.229)	(0.006)	(0.009)
Energy & Utilities	1.119***	0.007***	0.029***
	(0.054)	(0.002)	(0.003)
Financials	0.942***	0.024***	0.016***
	(0.016)	(0.001)	(0.001)
Healthcare	1.236***	0.013***	0.035***
	(0.072)	(0.002)	(0.002)
Industrials	1.321***	0.003***	0.039***
	(0.016)	(0.001)	(0.002)
Technology	1.499***	-0.015***	0.042***
	(0.032)	(0.001)	(0.001)
MKT		1.067***	
		(0.009)	
SMB		0.800***	
		(0.011)	
HML		-0.093***	
		(0.012)	
RMW		-0.241***	
		(0.014)	
CMA		0.245***	
		(0.016)	
UMD		-0.073***	
		(0.007)	
Observations	1,149,060	536,883	536,883

Table 14 reports firm-level regressions of the three monthly downside risk measures on brand equity. The dependent variable is the downside beta, downside excess return, or semi-variance at the firm-level. SBF = strong brand firms. A dummy variable equals 1 for strong brand firms and 0 for weak brand firms. The coefficient on this dummy, SBF, measures the difference in downside risk between strong and weak brand firms. Standard errors are clustered at the firm-level to account for within-firm dependence. To adjust for cross-sector heterogeneity, all firm-level regressions include industry fixed effects. Specifications with downside excess return additionally incorporate the Fama-French six factors to control for common sources of systematic risk. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Link back to portfolio-level (Table 5).

Table 15: Firm-level regression results of the relationship between brand equity and the three measures of downside risk moderated by crisis

	Downside beta	*Downside excess return*	*Semi-variance*
SBF	-0.159** (0.073)	0.006** (0.002)	-0.026*** (0.002)
SBF × DotCom	-0.179* (0.093)	0.013** (0.006)	-0.008*** (0.002)
SBF × GFC	0.011 (0.076)	0.001 (0.006)	-0.001 (0.003)
SBF × COVID	-0.307*** (0.060)	0.033*** (0.008)	-0.036*** (0.010)
SBF × Energy shock	-0.737*** (0.102)	-0.001 (0.004)	-0.006** (0.003)
DotCom	0.205*** (0.018)	0.009*** (0.001)	0.014*** (0.002)
GFC	0.153*** (0.019)	-0.005*** (0.001)	0.009*** (0.002)
COVID	0.235*** (0.022)	-0.010*** (0.003)	0.038*** (0.010)
Energy shock	0.560*** (0.029)	-0.011*** (0.001)	0.009*** (0.003)
Communication Services	1.120*** (0.095)	0.008*** (0.003)	0.021*** (0.003)
Consumer Discretionary	1.214*** (0.041)	0.009*** (0.001)	0.029*** (0.008)
Consumer Staples	0.601*** (0.230)	0.018*** (0.006)	0.024*** (0.009)
Energy & Utilities	1.049*** (0.054)	0.008*** (0.002)	0.025*** (0.003)
Financials	0.870*** (0.016)	0.025*** (0.001)	0.010*** (0.001)
Healthcare	1.165*** (0.072)	0.013*** (0.002)	0.030*** (0.002)
Industrials	1.244*** (0.017)	0.004*** (0.001)	0.033*** (0.002)
Technology	1.419*** (0.032)	-0.015*** (0.001)	0.037*** (0.002)
MKT		1.041*** (0.009)	
SMB		0.774*** (0.011)	
HML		-0.090*** (0.013)	
RMW		-0.341*** (0.014)	
CMA		0.215*** (0.017)	
UMD		-0.074*** (0.007)	
Observations	1,149,060	536,883	536,883

Table 15 reports time-series OLS regressions of monthly firm-level downside beta, downside excess return, and semi-variance on a strong brand indicator, crisis-period dummies, and their interactions. Crisis indicators (*DotCom*, *GFC*, *COVID*, *ES*) equal 1 within their respective windows and 0 otherwise. Interaction terms (*SBF × Crisis*) capture the incremental effect of strong brand firms during crisis periods. SBF = strong brand firms. The baseline coefficient on the strong brand dummy, SBF, measures the difference in downside risk between strong and weak brand firms outside of crisis periods. Coefficients on the crisis-period dummies capture how downside risk changes during crises relative to non-crisis months, while the interaction coefficients indicate whether the risk differential between strong and weak brand firms varies depending on the crisis mechanism. Standard errors are clustered at the firm-level to account for within-firm dependence. To adjust for cross-sector heterogeneity, all firm-level regressions include industry fixed effects. Specifications with downside excess return additionally incorporate the Fama-French six factors to control for common sources of systematic risk. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Link back to portfolio-level (Table 6).

Table 16: Firm-level regression results of the relationship between brand equity and the three measures of downside risk moderated by crisis (alternative definition)

	Downside beta	*Downside excess return*	*Semi-variance*
SBF	-0.122 (0.075)	0.009*** (0.003)	-0.022*** (0.001)
SBF × DotCom	-0.207** (0.090)	0.002 (0.006)	-0.015*** (0.002)
SBF × GFC	-0.029 (0.063)	-0.001 (0.005)	-0.002 (0.002)
SBF × COVID	-0.421*** (0.069)	0.009* (0.005)	-0.024*** (0.006)
SBF × Energy shock	-0.785*** (0.107)	-0.017*** (0.004)	-0.030*** (0.010)
DotCom	0.232*** (0.018)	0.017*** (0.001)	0.021*** (0.001)
GFC	0.127*** (0.017)	-0.000 (0.001)	0.008*** (0.001)
COVID	0.343*** (0.025)	-0.006*** (0.002)	0.027*** (0.006)
Energy shock	0.603*** (0.030)	-0.003*** (0.001)	0.033*** (0.010)
Communication Services	1.088*** (0.095)	0.007*** (0.003)	0.017*** (0.003)
Consumer Discretionary	1.183*** (0.042)	0.008*** (0.001)	0.025*** (0.007)
Consumer Staples	0.569** (0.229)	0.017*** (0.006)	0.020** (0.009)
Energy & Utilities	1.018*** (0.054)	0.007*** (0.002)	0.021*** (0.003)
Financials	0.839*** (0.017)	0.024*** (0.001)	0.007*** (0.001)
Healthcare	1.135*** (0.072)	0.012*** (0.002)	0.026*** (0.003)
Industrials	1.211*** (0.018)	0.003*** (0.001)	0.029*** (0.001)
Technology	1.386*** (0.032)	-0.016*** (0.001)	0.032*** (0.002)
MKT		1.065*** (0.009)	
SMB		0.747*** (0.011)	
HML		-0.098*** (0.013)	
RMW		-0.373*** (0.015)	
CMA		0.186*** (0.016)	
UMD		-0.089*** (0.007)	
Observations	1,149,060	536,883	536,883

Table 16 reports firm-level OLS regressions of monthly downside beta, downside excess return, and semi-variance on a strong brand indicator, crisis-period dummies, and their interactions under an alternative crisis definition. Crisis indicators (*DotCom*, *GFC*, *COVID*, *ES*) equal 1 within their respective windows and 0 otherwise. SBF = strong brand firms. Interaction terms (*SBF × Crisis*) capture the incremental effect of strong brand firms during crisis periods relative to non-crisis months.The coefficient on the strong brand dummy, SBF, reflects the difference in downside risk between strong and weak brand firms outside of crisis periods. Crisis-period coefficients capture how downside risk shifts during crises, while interaction coefficients show whether this risk differential changes across crises with distinct mechanisms.Standard errors are clustered at the firm-level to account for within-firm dependence. To adjust for cross-sector heterogeneity, all firm-level regressions include industry fixed effects. Specifications with downside excess return additionally incorporate the Fama-French six factors to control for common sources of systematic risk. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Link back to portfolio-level (Table 8).

Table 17: Firm-level regression results of the relationship between brand equity and the three measures of downside risk (without the years 1998 and 1999)

	Downside beta	*Downside excess return*	*Semi-variance*
SBF	-0.229***	0.009***	-0.028***
	(0.070)	(0.003)	(0.002)
Communication Services	1.177***	0.006**	0.021***
	(0.098)	(0.003)	(0.002)
Consumer Discretionary	1.289***	0.009***	0.034***
	(0.043)	(0.001)	(0.009)
Consumer Staples	0.646***	0.021**	0.026***
	(0.241)	(0.008)	(0.008)
Energy & Utilities	1.115***	0.002	0.029***
	(0.055)	(0.002)	(0.003)
Financials	0.937***	0.023***	0.014***
	(0.016)	(0.001)	(0.000)
Healthcare	1.237***	0.013***	0.030***
	(0.074)	(0.002)	(0.002)
Industrials	1.321***	0.000	0.037***
	(0.017)	(0.001)	(0.002)
Technology	1.475***	-0.013***	0.037***
	(0.032)	(0.001)	(0.001)
MKT		1.075***	
		(0.010)	
SMB		0.775***	
		(0.013)	
HML		-0.069***	
		(0.013)	
RMW		-0.165***	
		(0.014)	
CMA		0.123***	
		(0.018)	
UMD		-0.044***	
		(0.008)	
Observations	1,094,344	451,900	451,900

Table 17 reports firm-level regressions of monthly downside beta, downside excess return, and semi-variance on brand equity, excluding the years 1998 and 1999. The dependent variable is the downside risk measure at the firm-level. A dummy variable equals 1 for strong brand firms and 0 for weak brand firms. The coefficient on this dummy captures the difference in downside risk between strong and weak brand firms under the adjusted ranking sample.The exclusion of early ranking years mitigates structural differences in sample composition and assesses whether previous results are driven by initial data availability. Standard errors are clustered at the firm-level to allow for arbitrary within-firm dependence. SBF = strong brand firms. To adjust for cross-sector heterogeneity, all firm-level regressions include industry fixed effects. Specifications with downside excess return additionally incorporate the Fama-French six factors to control for common sources of systematic risk. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Link back to portfolio-level (Table 9).

Table 18: Firm-level regression results of the relationship between brand equity and the three measures of downside risk (alternative brand measure method)

	Downside beta	*Downside excess return*	*Semi-variance*
SBF	0.012	-0.001	-0.020***
	(0.053)	(0.002)	(0.002)
Communication Services	1.190***	0.008***	0.026***
	(0.095)	(0.003)	(0.003)
Consumer Discretionary	1.283***	0.009***	0.035***
	(0.041)	(0.001)	(0.008)
Consumer Staples	0.676***	0.018***	0.031***
	(0.229)	(0.006)	(0.009)
Energy & Utilities	1.119***	0.007***	0.029***
	(0.054)	(0.002)	(0.003)
Financials	0.940***	0.024***	0.015***
	(0.016)	(0.001)	(0.001)
Healthcare	1.236***	0.013***	0.035***
	(0.072)	(0.002)	(0.002)
Industrials	1.318***	0.004***	0.039***
	(0.016)	(0.001)	(0.002)
Technology	1.494***	-0.015***	0.042***
	(0.032)	(0.001)	(0.001)
MKT		1.067***	
		(0.009)	
SMB		0.800***	
		(0.011)	
HML		-0.093***	
		(0.012)	
RMW		-0.242***	
		(0.014)	
CMA		0.245***	
		(0.016)	
UMD		-0.073***	
		(0.007)	
Observations	1,149,060	536,883	536,883

Table 18 reports firm-level OLS estimates of monthly downside beta, downside excess return, and semi-variance as a function of a strong brand indicator derived from an alternative brand measure. The indicator equals 1 for firms identified as strong brands under this measure and 0 otherwise. The coefficient on the indicator represents the difference in downside risk between strong and weak brand firms conditional on the revised classification scheme. This alternative specification evaluates the sensitivity of our results to brand measurement choices. Standard errors are clustered at the firm-level to allow for arbitrary within-firm dependence. SBF = strong brand firms. To adjust for cross-sector heterogeneity, all firm-level regressions include industry fixed effects. Specifications with downside excess return additionally incorporate the Fama-French six factors to control for common sources of systematic risk. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Link back to portfolio-level (Table 10).

Table 19: Firm-level regression results of the relationship between brand equity and the downside risk measures moderated by crisis (alternative brand measure method)

	Downside beta	*Downside excess return*	*Semi-variance*
SBF	0.037 (0.053)	-0.000 (0.002)	-0.017*** (0.002)
SBF × DotCom	-0.177 (0.330)	0.001 (0.019)	-0.000 (0.007)
SBF × GFC	0.189* (0.104)	-0.001 (0.005)	0.002 (0.003)
SBF × COVID	-0.148* (0.081)	-0.013 (0.010)	-0.030*** (0.010)
SBF × Energy shock	-0.312*** (0.114)	0.013*** (0.005)	-0.010*** (0.004)
DotCom	0.205*** (0.018)	0.009*** (0.001)	0.014*** (0.002)
GFC	0.149*** (0.020)	-0.005*** (0.001)	0.010*** (0.002)
COVID	0.234*** (0.022)	-0.009*** (0.003)	0.039*** (0.010)
Energy shock	0.559*** (0.029)	-0.011*** (0.001)	0.009*** (0.003)
Communication Services	1.120*** (0.095)	0.008*** (0.003)	0.021*** (0.003)
Consumer Discretionary	1.208*** (0.041)	0.009*** (0.001)	0.029*** (0.008)
Consumer Staples	0.597** (0.232)	0.018*** (0.006)	0.025*** (0.009)
Energy & Utilities	1.050*** (0.054)	0.008*** (0.002)	0.025*** (0.003)
Financials	0.869*** (0.016)	0.025*** (0.001)	0.010*** (0.001)
Healthcare	1.165*** (0.072)	0.013*** (0.002)	0.030*** (0.002)
Industrials	1.241*** (0.017)	0.004*** (0.001)	0.033*** (0.002)
Technology	1.414*** (0.032)	-0.015*** (0.001)	0.036*** (0.002)
MKT		1.041*** (0.009)	
SMB		0.774*** (0.011)	
HML		-0.090*** (0.013)	
RMW		-0.341*** (0.014)	
CMA		0.215*** (0.017)	
UMD		-0.074*** (0.007)	
Observations	1,149,060	536,883	536,883

Table 19 reports firm-level regressions of monthly downside beta, downside excess return, and semi-variance on an alternative brand measure, crisis-period dummies, and their interactions. Crisis indicators (*DotCom*, *GFC*, *COVID*, *ES*) equal 1 within their respective windows and 0 otherwise. SBF = strong brand firms. Interaction terms (*SBF × Crisis*) identify whether the risk differential between strong and weak brand firms varies during crisis periods when using the alternative brand identification method. The strong brand coefficient represents the difference in downside risk outside of crises, while crisis and interaction coefficients describe crisis-specific adjustments in both the level and distribution of downside risk. Standard errors are clustered at the firm-level. To adjust for cross-sector heterogeneity, all firm-level regressions include industry fixed effects. Specifications with downside excess return additionally incorporate the Fama-French six factors to control for common sources of systematic risk. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Link back to portfolio-level (Table 11).

A.6 Alternative Brand Measure Method Extension

A.6.1 Expanded Data Description and Methodology

As a further robustness check, we use Boustanifar and Kang's (2025) text-based measure. We count the amount of times the word "brand" or similar is used in the annual filings of U.S. listed companies. The underlying logic is that if a brand would be a core element of a business's strategy, it would appear more often in the filings of the company.

We introduce multiple enhancements of the measure in order to improve accuracy. This includes that we will not only search through the reports based on the keyword "brand", but we will also consider "brands", "branded", "branding", "trademark", "trademarks", "label", "logo" and "logos". We treat these terms as being similar to the word brand and assume them to have a similar effect. As another control, we also consider both the entire filing and the business section of the filing separately and normalize by 10,000 words for both. We do this as we understand that one of the biggest downsides of this measure might be the overinterpretation of these terms used or them just being named as legal terms. A third adjustment we make is that companies that include the word "brand" in their business name will be excluded from this measure, as this would lead to an overinterpretation.

We collect this data with a webscraping file that reads the annual filings of all entries in our stock universe. From this data, we then create yearly strong brand portfolio out of the leading 100 firms with the highest brand counts and run the same analyses as for the Interbrand portfolio.

Link back to methodology (3).

A.6.2 Composition of the Value-Weighted Portfolio 2024 Constructed by Using the Alternative Brand Measure

Figure 8: Value-weighted portfolio composition 2024

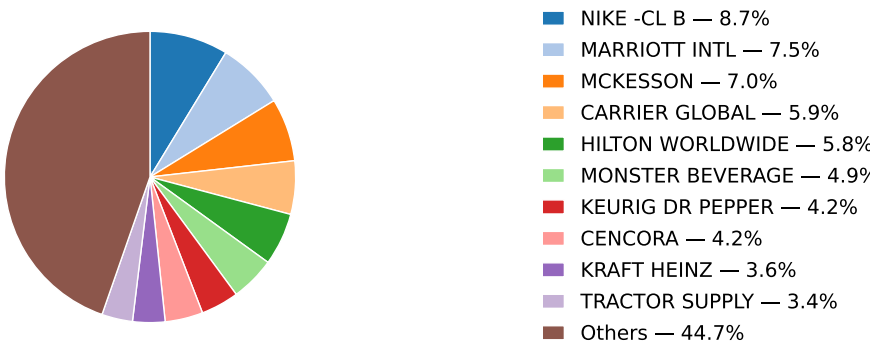


Figure 8 visualizes the composition of the value-weighted portfolio 2024 constructed using the alternative brand measure.