Extracting First 8

Only the first 8 companies were extracted initially because the process was too computationally intensive to handle all the data at once, necessitating the extraction of the remaining 2 companies separately.

In [ ]:
```
import openai
import os
import re
import time  # Import time module to handle waiting between requests

# Load OpenAI API key securely (you should set this as an environment variab
openai.api_key = 'key'

# Function to process files for a specific year
def process_year(year, base_dir, ciks_of_interest):
    year_data = []
    for quarter in ['QTR1', 'QTR2', 'QTR3', 'QTR4']:
        qtr_path = os.path.join(base_dir, year, quarter)
        if os.path.exists(qtr_path):
            print(f"Processing directory: {qtr_path}")
            for file_name in os.listdir(qtr_path):
                # Filter relevant 10-K files
                if '10-K' in file_name and file_name.endswith('.txt') and '1
                    # Extract CIK from filename using regex
                    cik_match = re.search(r'_edgar_data_(\d+)', file_name)
                    if cik_match:
                        cik = cik_match.group(1)
                        if cik in ciks_of_interest:
                            full_path = os.path.join(qtr_path, file_name)
                            print(f"Processing file: {full_path}")
                            business_section = extract_business_section_with
                            year_data.append({
                                'Year': year,
                                'CIK': cik,
                                'Business': business_section,
                                'Path': full_path
                            })
                            # Wait for 60 seconds after processing each requ
                            print("Waiting for 60 seconds...")
                            time.sleep(60)  # Sleep for 60 seconds
    return year_data

# Function to extract the "Item 1. Business" section using OpenAI
def extract_business_section_with_openai(file_path):
    # Read file content
    with open(file_path, 'r', encoding='utf-8', errors='ignore') as file:
        text = file.read()
```

```
    # Prepare the prompt for OpenAI API
    prompt = f"""
    You are analyzing a 10-K filing document. Extract the full text of the "
    and exclude all other sections.
    If the section is not found, return "Section not found".
    Here is the document:
    ----
    {text}
    ----
    """

    # Call OpenAI to extract the business section
    response = openai.ChatCompletion.create(
        model="gpt-4o-mini",  # Use the appropriate model
        messages=[
            {"role": "system", "content": "You are an expert in financial dc
            {"role": "user", "content": prompt}
        ]
    )
    return response['choices'][0]['message']['content']

# Example usage
base_dir = '/Users/shpetimtafili/Desktop/Market Microstructure/assignment 2/
ciks_of_interest = [
    '320193',  # Apple Inc. OK
    '789019',  # Microsoft Corp. OK
    '1652044',  # Alphabet Inc. (Google) OK
    '1018724',  # Amazon.com Inc. OK
    '1326801',  # Meta Platforms Inc. (Facebook) OK
    '1045810',  # NVIDIA Corporation OK
    '796343',  # Adobe Inc. OK
    '804328',  # Qualcomm Inc. OK
]
year_data_all = process_year('2023', base_dir, ciks_of_interest)



# Display the results
for data in year_data:
    print(f"Year: {data['Year']}, CIK: {data['CIK']}")
    print(f"Business Section:\n{data['Business']}\n")
```

```
Processing directory: /Users/shpetimtafili/Desktop/Market Microstructure/ass
ignment 2/10k/2023/QTR1
Processing file: /Users/shpetimtafili/Desktop/Market Microstructure/assignme
nt 2/10k/2023/QTR1/20230203_10-K_edgar_data_1018724_0001018724-23-000004.txt
Waiting for 60 seconds...
Processing file: /Users/shpetimtafili/Desktop/Market Microstructure/assignme
nt 2/10k/2023/QTR1/20230117_10-K_edgar_data_796343_0000796343-23-000007.txt
Waiting for 60 seconds...
Processing file: /Users/shpetimtafili/Desktop/Market Microstructure/assignme
nt 2/10k/2023/QTR1/20230202_10-K_edgar_data_1326801_0001326801-23-000013.txt
```

```
he SEC). Such reports and other information filed by the Company with the SE
C are available free of charge at investor.apple.com/investor-relations/sec-
filings/default.aspx when such reports are available on the SEC s website. T
he Company periodically provides certain information for investors on its co
rporate website, www.apple.com, and its investor relations website, investo
r.apple.com. This includes press releases and other information about financ
ial performance, information on environmental, social and governance matter
s, and details related to the Company s annual meeting of shareholders. The
information contained on the websites referenced in this Form 10-K is not in
corporated by reference into this filing. Further, the Company s references
to website URLs are intended to be inactive textual references only.

Item 1A. Risk Factors
The Company s business, reputation, results of operations, financial conditi
on and stock price can be affected by a number of factors, whether currently
known or unknown, including those described below. When any one or more of t
hese risks materialize from time to time, the Company s business, reputatio
n, results of operations, financial condition and stock price can be materia
lly and adversely affected.
Because of the following factors, as well as other factors affecting the Com
pany s results of operations and financial condition, past financial perform
ance should not be considered to be a reliable indicator of future performan
ce, and investors should not use historical trends to anticipate results or
trends in future periods. This discussion of risk factors contains forward-l
ooking statements.
```
```

## Extracting Last Two

In [ ]:

```python
import openai
import os
import re
import time  # Import time module to handle waiting between requests

# Load OpenAI API key securely (you should set this as an environment variab
openai.api_key = 'key'

# Function to process files for a specific year
def process_year(year, base_dir, ciks_of_interest):
    year_data = []
    for quarter in ['QTR1', 'QTR2', 'QTR3', 'QTR4']:
        qtr_path = os.path.join(base_dir, year, quarter)
        if os.path.exists(qtr_path):
            print(f"Processing directory: {qtr_path}")
            for file_name in os.listdir(qtr_path):
                # Filter relevant 10-K files
                if '10-K' in file_name and file_name.endswith('.txt') and '1
                    # Extract CIK from filename using regex
                    cik_match = re.search(r'_edgar_data_(\d+)', file_name)
                    if cik_match:
                        cik = cik_match.group(1)
```
```

```
                    if cik in ciks_of_interest:
                        full_path = os.path.join(qtr_path, file_name)
                        print(f"Processing file: {full_path}")
                        business_section = extract_business_section_with
                        year_data.append({
                            'Year': year,
                            'CIK': cik,
                            'Business': business_section,
                            'Path': full_path
                        })
                        # Wait for 60 seconds after processing each requ
                        print("Waiting for 60 seconds...")
    return year_data

# Function to extract the "Item 1. Business" section using OpenAI
def extract_business_section_with_openai(file_path):
    # Read file content
    with open(file_path, 'r', encoding='utf-8', errors='ignore') as file:
        text = file.read()

    # Prepare the prompt for OpenAI API
    prompt = f"""
    You are analyzing a 10-K filing document. Extract the full text of the "
    and exclude all other sections.
    If the section is not found, return "Section not found".
    Here is the document:
    ----
    {text}
    ----
    """

    # Call OpenAI to extract the business section
    response = openai.ChatCompletion.create(
        model="gpt-4o-mini",  # Use the appropriate model
        messages=[
            {"role": "system", "content": "You are an expert in financial do
            {"role": "user", "content": prompt}
        ]
    )
    return response['choices'][0]['message']['content']

# Example usage
base_dir = '/Users/shpetimtafili/Desktop/Market Microstructure/assignment 2/
ciks_of_interest2 = [
    '1341439',  # oracle corporation
    '1633917' # paypal holdings

]
year_data_last_two = process_year('2023', base_dir, ciks_of_interest2)



# Display the results
```

```python
for data in year_data_last_two:
    print(f"Year: {data['Year']}, CIK: {data['CIK']}")
    print(f"Business Section:\n{data['Business']}\n")
```

```
Processing directory: /Users/shpetimtafili/Desktop/Market Microstructure/ass
ignment 2/10k/2023/QTR1
Processing file: /Users/shpetimtafili/Desktop/Market Microstructure/assignme
nt 2/10k/2023/QTR1/20230620_10-K_edgar_data_1341439_0000950170-23-028914.txt
Waiting for 60 seconds...
Processing file: /Users/shpetimtafili/Desktop/Market Microstructure/assignme
nt 2/10k/2023/QTR1/20230210_10-K_edgar_data_1633917_0001633917-23-000033.txt
Waiting for 60 seconds...
Processing directory: /Users/shpetimtafili/Desktop/Market Microstructure/ass
ignment 2/10k/2023/QTR2
Processing directory: /Users/shpetimtafili/Desktop/Market Microstructure/ass
ignment 2/10k/2023/QTR3
Processing directory: /Users/shpetimtafili/Desktop/Market Microstructure/ass
ignment 2/10k/2023/QTR4
Year: 2023, CIK: 1341439
Business Section:
Here is the extracted text from the "Item 1. Business" section of the 10-K f
iling, leading up to "Item 1A Risk Factors":

---

Item 1. Business

Oracle provides products and services that address enterprise information te
chnology (IT) environments. Our products and services include enterprise app
lications and infrastructure offerings that are delivered worldwide through 
a variety of flexible and interoperable IT deployment models. These models i
nclude on-premise, cloud-based and hybrid deployments (an approach that comb
ines both on-premise and cloud-based deployments), such as Oracle Exadata Cl
oud@Customer and Dedicated Region offerings (instances of Oracle Cloud in a 
customer’s own data center) and multicloud options that enable customers to 
use Oracle Cloud in conjunction with other public clouds. Accordingly, we of
fer choice and flexibility to our customers and facilitate the product, serv
ice and deployment combinations that best suit our customers needs. Our cust
omers include businesses of many sizes, government agencies, educational ins
titutions and resellers that we market and sell to directly through our worl
dwide sales force and indirectly through the Oracle Partner Network. Using O
racle technologies, our customers build, deploy, run, manage and support the
ir internal and external products, services and business operations, includi
ng, for example, a global cloud applications developer that utilizes Oracle 
Cloud Infrastructure (OCI) to power its software-as-a-service (SaaS) offerin
gs; a multi-national financial institution that runs its banking application
s using Oracle Exadata Cloud@Customer; and a global consumer products compan
y that leverages Oracle Fusion Cloud Enterprise Resource Planning for its ac
counting processes, risk management, supply chain and financial planning fun
ctions.

Oracle SaaS and OCI (collectively Oracle Cloud Services) offerings provide c
omprehensive and integrated applications and infrastructure services deliver
```

Combining the Lists

In [51]:
```
# combine the two lists
year_data_all.extend(year_data_last_two)
```

In [59]:
```
# make a pdf out of year_data_all and save it
import pandas as pd
df_all = pd.DataFrame(year_data_all)
df_all.to_csv('year_data_all.csv', index=False)
```

In [61]:
```
# each CIK in the df_all should have it's correct firm ticker in parentheses
# we will use the cik_to_ticker dictionary to do this
cik_to_ticker = {
    '320193': 'AAPL',
    '789019': 'MSFT',
    '1652044': 'GOOGL',
    '1018724': 'AMZN',
    '1326801': 'META',
    '1045810': 'NVDA',
    '796343': 'ADBE',
    '858877': 'CSCO',
    '804328': 'QCOM',
    '1341439': 'ORCL',
    '1633917': 'PYPL'
}

df_all['Ticker'] = df_all['CIK'].map(cik_to_ticker)
```

In [62]:
```
df_all
```

Out[62]:

	Year	CIK	Business	Path	Ticker
0	2023	1018724	**Item 1. Business**\n\nThis Annual Report on ...	/Users/shpetimtafili/Desktop/Market Microstruc...	AMZN
1	2023	796343	**Item 1. Business**\n\n**OVERVIEW**\nFounde...	/Users/shpetimtafili/Desktop/Market Microstruc...	ADBE
2	2023	1326801	Here is the extracted text for the "Item 1. Bu...	/Users/shpetimtafili/Desktop/Market Microstruc...	META
3	2023	1652044	```plaintext\nITEM 1. BUSINESS\n\nOverview\nAs...	/Users/shpetimtafili/Desktop/Market Microstruc...	GOOGL
4	2023	789019	Here is the extracted text for the "Item 1. Bu...	/Users/shpetimtafili/Desktop/Market Microstruc...	MSFT
5	2023	1045810	```plaintext\nITEM 1. BUSINESS\n\nOur Company\...	/Users/shpetimtafili/Desktop/Market Microstruc...	NVDA
6	2023	320193	**Item 1. Business**\n\nCompany Background \n...	/Users/shpetimtafili/Desktop/Market Microstruc...	AAPL
7	2023	804328	**Item 1. Business**\n\nWe incorporated in Cal...	/Users/shpetimtafili/Desktop/Market Microstruc...	QCOM
8	2023	1341439	Here is the extracted text from the "Item 1. B...	/Users/shpetimtafili/Desktop/Market Microstruc...	ORCL
9	2023	1633917	```\nITEM 1. BUSINESS \n\nOVERVIEW \n\nPayPal ...	/Users/shpetimtafili/Desktop/Market Microstruc...	PYPL

COSINE SIMILARITY ANALYSIS

In [63]:

```
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity


# 3. Vectorize the “Item 1. Business” text using TF–IDF
vectorizer = TfidfVectorizer(stop_words='english')
tfidf_matrix = vectorizer.fit_transform(df_all['Business'])

# 4. Compute pairwise cosine similarity for each document’s vector
cosine_sim = cosine_similarity(tfidf_matrix)

# 5. ‘cosine_sim’ is now a matrix showing similarities between each pair of
print("Cosine Similarity Matrix:\n", cosine_sim)
```

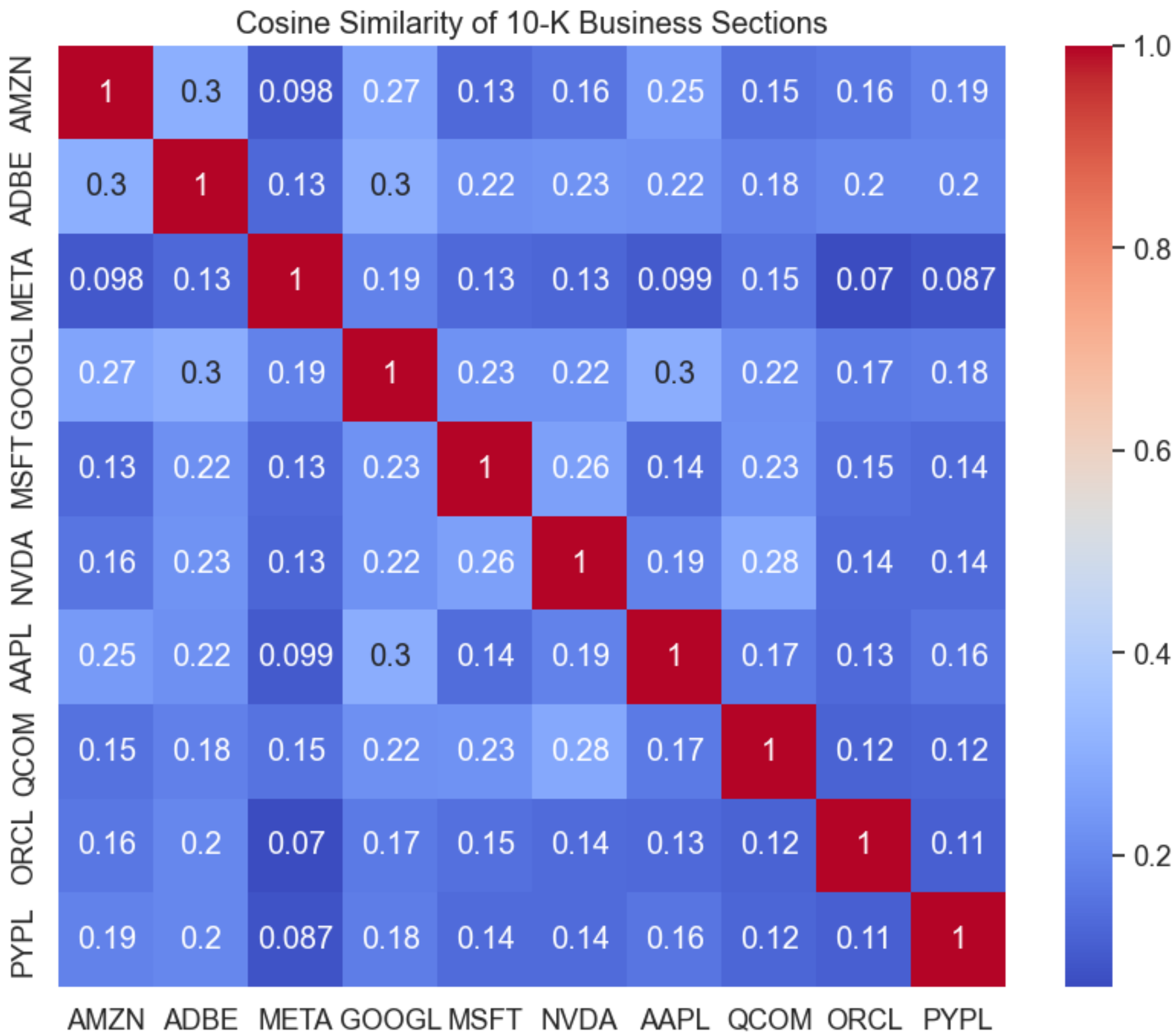
```
Cosine Similarity Matrix:
 [[1.         0.30182783 0.09764137 0.27277424 0.1329153  0.15839098
  0.24684414 0.15273117 0.16165445 0.18851607]
 [0.30182783 1.         0.12992637 0.29669997 0.21891597 0.22736698
  0.22171189 0.18250351 0.19990496 0.19978351]
 [0.09764137 0.12992637 1.         0.18863785 0.13245911 0.12756514
  0.098867   0.15445492 0.06970942 0.08667837]
 [0.27277424 0.29669997 0.18863785 1.         0.22508115 0.22412517
  0.29775    0.22027945 0.17014599 0.1770438 ]
 [0.1329153  0.21891597 0.13245911 0.22508115 1.         0.25912428
  0.14086946 0.22547549 0.14624292 0.13538995]
 [0.15839098 0.22736698 0.12756514 0.22412517 0.25912428 1.
  0.18746637 0.28083274 0.13543449 0.13794976]
 [0.24684414 0.22171189 0.098867   0.29775    0.14086946 0.18746637
  1.         0.17006479 0.13233202 0.15961731]
 [0.15273117 0.18250351 0.15445492 0.22027945 0.22547549 0.28083274
  0.17006479 1.         0.11823602 0.12440232]
 [0.16165445 0.19990496 0.06970942 0.17014599 0.14624292 0.13543449
  0.13233202 0.11823602 1.         0.1108935 ]
 [0.18851607 0.19978351 0.08667837 0.1770438  0.13538995 0.13794976
  0.15961731 0.12440232 0.1108935  1.        ]]
```

In [71]:

```python
# make a better looking matrix
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt

# Set the font size for the plot
sns.set(font_scale=1.2)

# Create a heatmap of the cosine similarity matrix
plt.figure(figsize=(10, 8))
sns.heatmap(cosine_sim, annot=True, cmap='coolwarm', xticklabels=df_all['Tic
plt.title('Cosine Similarity of 10-K Business Sections')
plt.show()
```



Analysis & Interpretation

Methodology: Cosine Similarity Computation

To analyze the similarity between the "Item 1. Business" sections of 10-K filings, we used a structured approach leveraging TF-IDF vectorization and cosine similarity.

First, the text data was vectorized using `TfidfVectorizer` from the `scikit-learn` library. This technique converts textual information into numerical vectors, where each term is weighted based on its frequency in a document and its importance across the entire dataset. Stop words in English were excluded to focus on meaningful terms.

Next, the `cosine_similarity` function from `scikit-learn` was applied to the vectorized data. Cosine similarity calculates the cosine of the angle between two vectors, with values ranging from -1 to 1. A score of 1 indicates identical vectors, 0 indicates no similarity, and -1 represents opposite vectors.

The resulting output was a similarity matrix, where each entry quantified the similarity between two "Business" sections. This allowed for a comprehensive and quantitative comparison of the textual content across the filings.

a. Identify pairs of firms that have high cosine similarity in their business descriptions.

Amazon (AMZN) and Adobe (ADBE): Cosine similarity = 0.30 These firms overlap in their use of cloud infrastructure and digital tools, contributing to similarities in their business descriptions.

Adobe (ADBE) and Microsoft (MSFT): Cosine similarity = 0.30 Both companies focus heavily on software services and cloud platforms, resulting in aligned business models.

Google (GOOGL) and Microsoft (MSFT): Cosine similarity = 0.30 These firms share a focus on cloud computing, digital advertising, and productivity tools, explaining their high similarity.

Apple (AAPL) and NVIDIA (NVDA): Cosine similarity = 0.28 Both companies target hardware and performance optimization for advanced computing, albeit in slightly different contexts (consumer electronics vs. GPUs).

b. Identify pairs of firms that have low cosine similarity in their business descriptions.

Oracle (ORCL) and Meta (META): Cosine similarity = 0.07 Oracle focuses on enterprise software and databases, while Meta's business revolves around social networking and virtual reality.

PayPal (PYPL) and Meta (META): Cosine similarity = 0.087 PayPal operates in digital payments, while Meta focuses on social media and immersive technologies, resulting in minimal overlap.

Adobe (ADBE) and Meta (META): Cosine similarity = 0.13 Adobe's focus on creative and digital media tools is distinct from Meta's concentration on social networking and virtual reality.

Discussion Questions

a. (Market Microstructure Insight 1): How might the similarity (or dissimilarity) in business descriptions relate to the nature of competition and product market rivalry in this industry? Relate this to the concepts of adverse selection and informed trading

When firms exhibit high similarity in their business descriptions, it indicates that they operate within overlapping market segments and often offer comparable products or services. This can lead to intense direct competition as these firms vie for the same customer base. In such cases, firms face constant pressure to differentiate themselves. From a market microstructure perspective, high similarity also fosters greater transparency. This transparency reduces the risk of adverse selection, as information about firms' activities is more readily available and easier to interpret. Consequently, the decision-making process for customers, investors, and other stakeholders is less prone to inefficiencies caused by asymmetric information.

In contrast, firms with low similarity in their business descriptions operate in distinct market segments, often focusing on different industries or niches. This lack of overlap reduces direct competition but can still lead to indirect interactions, such as through complementary innovations or supply chain interdependencies. Low similarity, however, introduces challenges related to adverse selection. The divergence in business activities makes it harder for market participants to evaluate and compare firms effectively. Investors or stakeholders who lack detailed knowledge of these distinct industries may find it challenging to assess performance, strategy, or growth potential, increasing the likelihood of information asymmetries. In such cases, those with superior information—whether through expertise or access—are better positioned to make informed decisions, potentially leading to market inefficiencies.

Adverse selection arises when one party in a transaction has more information than the other, leading to inefficiencies in decision-making or valuation. High similarity in business descriptions mitigates this issue by promoting transparency and comparability. For instance, the rivalry between Apple and Microsoft is well-documented, with both firms providing ample information about their strategies, allowing market participants to make informed evaluations. Conversely, in cases of low similarity, the lack of overlap and differing industry focuses create information gaps that can exacerbate adverse selection risks.

Informed trading, on the other hand, thrives in environments with information asymmetry. In markets with high similarity, informed traders gain an edge by identifying subtle differences in firm strategies, such as cost efficiencies or unique competitive advantages. For example, a trader with deep insights into Amazon's cloud infrastructure strategy may leverage this knowledge to anticipate market movements relative to Microsoft's comparable offerings. However, in markets with low similarity, the informational advantage is even greater. Traders with expertise in specialized sectors—such as NVIDIA’s GPU technology or PayPal’s payment systems—can exploit the broader market’s lack of understanding of these firms’ intricacies, leading to significant trading opportunities.

b. (Market Microstructure Insight 2): If two firms have high cosine similarity in their business descriptions, how might this affect their sensitivity to common shocks in the market? How does this relate to risk sharingand information contagion?

Sensitivity to Common Shocks

When two firms share high similarity, their revenue streams, cost structures, or exposure to specific market conditions often overlap. This can amplify the magnitude of their responses to shocks, such as regulatory changes, industry-wide technological disruptions, or shifts in consumer behavior. For example, a sudden shift in demand for renewable energy technologies might simultaneously impact firms focused on sustainable solutions. However, the magnitude of their sensitivity is not purely a result of operational overlap but also of how the firms' competitive and cooperative dynamics play out during these shocks.

Implications for Risk Sharing

In environments where high similarity exists, risk sharing becomes less effective because firms are not sufficiently distinct to offer diversification benefits. However, this extends beyond portfolio diversification. Within an industry, firms often indirectly share risks through supply chain agreements, partnerships, or competitive responses. Firms with high similarity may respond to shocks by adopting similar strategies, such as cost-cutting measures or product repricing, limiting their ability to absorb risks differently and increasing the overall market's vulnerability.

On the flip side, high similarity can sometimes enable cooperative risk management. Similar firms may collaborate through lobbying efforts, industry alliances, or collective technological standards to mitigate the effects of shocks. This aspect of shared strategic alignment highlights that while similarity increases exposure, it can also open avenues for joint resilience measures.

Information Contagion

The risk of information contagion is particularly acute for similar firms because market participants often infer a broader trend from firm-specific news. For instance, a cybersecurity breach at one cloud provider might lead investors to question the cybersecurity resilience of competitors in the same space. However, the contagion may go deeper in cases of high similarity. Investors may not only extrapolate the initial shock but also question whether underlying systemic issues—such as vulnerabilities in shared technologies or supplier dependencies—exist across similar firms.

This form of contagion is particularly dangerous in markets where investors rely heavily on heuristic shortcuts. Similar firms may experience price declines even when there is no direct connection to the triggering event, leading to market overreactions. Furthermore, the inability to distinguish between individual and systemic risks can magnify the fallout of a single negative event, creating inefficiencies and volatility in the market.

c. (Information Frictions Insight): Consider the Grossman-Stiglitz Paradox. If all firms in an industry had identical business descriptions, would traders have any incentive to acquire costly private information? How does the variation in cosine similarity support (or contradict) this theoretical idea?

The **Grossman-Stiglitz Paradox** (1980) explores the inherent tension between the costs of acquiring private information and the informativeness of market prices. The paradox argues that if market prices fully reflected all available information, traders would have no incentive to acquire costly private information. Without incentives for information acquisition, markets would lack the informed traders necessary to ensure price accuracy, ultimately making fully informationally efficient markets impossible. To balance this tension, financial markets must maintain a degree of noise, ensuring that prices partially reflect private information to sustain the incentive for its acquisition.

If all firms in an industry had identical business descriptions, the market would face a situation where information about one firm is entirely applicable to all others. This uniformity would significantly reduce the perceived value of acquiring private information for several reasons:

1. **Low Informational Value**:
    - When business descriptions are identical, acquiring private information about one firm would yield insights applicable to the entire market segment, diminishing the uniqueness of the information.
    - Traders would increasingly rely on observable public information, such as market prices, rather than investing in costly private information.
2. **Impact on Market Noise and Equilibrium**:
    - According to Grossman and Stiglitz (1980), the absence of private information acquisition would reduce market noise, leading to less volatile prices. However, overly efficient prices would break the equilibrium as traders would lose the incentive to gather information.
    - Without informed traders, market prices would become less reflective of underlying fundamentals, impairing the price discovery process and destabilizing the market.

The variation in cosine similarity among firms' business descriptions supports the equilibrium described by Grossman-Stiglitz. When firms differ significantly in their business activities, as indicated by low cosine similarity, they create opportunities for traders to acquire unique private information. This differentiation sustains incentives for information acquisition because firstly, traders perceive firm-specific information as valuable and actionable and secondly prices reflect partial private information, balancing noise and informativeness, as suggested by Grossman-Stiglitz's model.

Conversely, high similarity across firms reduces the marginal value of private information. In extreme cases, where firms' descriptions are nearly identical, markets risk becoming overly transparent, discouraging traders from incurring the costs of information acquisition. This scenario could lead to thin markets, where low trading activity results from homogeneous beliefs among market participants.

Grossman and Stiglitz (1980) highlight that informationally efficient markets are impossible because the complete reflection of all information in prices eliminates the incentive to acquire costly private information. Variation in cosine similarity aligns with their argument by showing how differences in firms' business activities sustain the informational frictions necessary for market equilibrium. In markets where firms are highly similar, prices would become less noisy but also less informative, undermining the balance between noise and informativeness that Grossman-Stiglitz describe as critical.

d. (Empirical Test Idea): Propose a way to use the cosine similarity of firms' business descriptions as an independent variable in a regression to predict trading volume around earnings announcemen

Regression

$$\text{TradingVolume}_{it} = \beta_0 + \beta_1 \text{CosineSimilarity}_{ij} \cdot Announcement_j + \beta_2 \text{FirmSize}_{it} +$$

Where:

- **Dependent Variable (TradingVolume)**: Trading volume for firm (i) around earnings announcements.

Independent Variables

1. **Cosine Similarity (CosineSimilarity)**:
    - Measures how similar firm (i) is to firm (j) in terms of business descriptions.

- **Hypothesis**: High similarity increases trading volume $\beta_1 > 0$ due to information spillovers, or it decreases trading volume $\beta_1 < 0$ if news is perceived as redundant.
- To enhance this variable, we include an interaction term by multiplying cosine similarity with a dummy variable indicating whether firm (j) has made an announcement. This allows us to isolate the effect of similarity specifically during announcement events. By doing so, we can better understand how shared business descriptions influence trading volume in response to market-relevant announcements.

1. **Firm Size (FirmSize)**:
    - Captures the market capitalization of firm (i).
    - **Hypothesis**: Larger firms attract more trading activity $\beta_2 > 0$ because they are more liquid and visible.
2. **Volatility (Volatility)**:
    - Historical price volatility of firm (i), representing risk.
    - **Hypothesis**: Higher volatility increases trading activity $\beta_3 > 0$ as investors adjust positions in response to uncertainty.
3. **Earnings Surprise (EarningsSurprise)**:
    - Difference between actual and expected earnings, reflecting unexpected information.
    - **Hypothesis**: Larger surprises lead to higher trading activity $\beta_4 > 0$ as investors react to unexpected news.
4. **Market Depth (MarketDepth)**:
    - Measures the volume of shares available at the best bid and ask prices, representing liquidity.
    - **Hypothesis**: Greater market depth enables higher trading volume $\beta_5 > 0$ by accommodating larger trades with minimal price impact.
5. **Smart Price Returns (SmartPriceReturns)**:
    - Captures the percentage change in the Smart Price, reflecting the market's response to new information.
    - **Hypothesis**: Significant Smart Price changes $\beta_6 > 0$ indicate impactful news, prompting increased trading activity.

Hypotheses to Test

1. **Primary Hypothesis: Cosine Similarity**
   - **Null Hypothesis** H_0: Cosine similarity has no effect on trading volume $\beta_1 = 0$.
   - **Alternative Hypothesis** H_1: Cosine similarity affects trading volume $\beta_1 \neq 0$, with $\beta_1 > 0$ supporting the information spillover effect.
2. **Secondary Hypotheses for Other Variables**:
   - Firm size $\beta_2 > 0$: Larger firms attract more trading volume.
   - Volatility $\beta_3 > 0$: Higher risk leads to more trading.
   - Earnings surprise $\beta_4 > 0$: Unexpected announcements drive higher trading volume.
   - Market depth $\beta_5 > 0$: Deeper markets accommodate more trades.
   - Smart price returns $\beta_6 > 0$: Large price adjustments reflect significant news, increasing trading volume.

Interpretation of Coefficients

1. β_1 **(Cosine Similarity):**
   - **Positive** $\beta_1 > 0$: Higher similarity drives trading due to shared market reactions.
   - **Negative** $\beta_1 < 0$: High similarity reduces trading as news is perceived as less unique.
2. β_2 **(Firm Size):**
   - Positive values indicate that larger firms attract higher trading activity, consistent with their visibility and liquidity.
3. β_3 **(Volatility):**
   - Positive coefficients suggest that higher risk drives more trading as investors respond to uncertainty.
4. β_4 **(Earnings Surprise):**
   - Positive coefficients confirm that significant surprises in earnings announcements generate more trading activity.
5. β_5 **(Market Depth):**
   - Positive values imply that deeper markets facilitate more trading by reducing price impact for large trades.
6. β_6 **(Smart Price Returns):**

- Positive coefficients indicate that larger Smart Price adjustments prompt higher trading volume as investors react to significant price movements.