THE RELATIONSHIP BETWEEN BITCOIN AND TRADITIONAL FINANCIAL ASSETS IN THE CONTEXT OF TRADING DECISIONS: A DCC-GARCH APPROACH WITH MACHINE LEARNING

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DOCTOR OF PHILOSOPHY
IN DIGITAL INNOVATION AND FINANCIAL TECHNOLOGY

CHIANG MAI UNIVERSITY
JANUARY 2024

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A THESIS SUBMITTED TO CHIANG MAI UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY IN DIGITAL INNOVATION AND FINANCIAL TECHNOLOGY

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31 January 2024

ACKNOWLEDGEMENT

I truly appreciate my dissertation mentor, Dr. Nathee Naktnasukanjn. His academic rigor, broad-mindedness as a human being, and selfless help in guiding the articles during the writing of my thesis gave me countless motivation during my PhD study. "Facing everything optimistically" and "treating everything seriously" not only gave me great motivation to finish my thesis, but also deeply influenced my future work and research.

I genuinely appreciate Dr. Anukul Tamprasirt, Dr.Tanarat Rattanadamrongaksorn and Dr. Siva Shankar Ramasamy, who have carefully revised my dissertation and given me a lot of focused suggestions. Their rich expertise and academic standard have been a great help to me. I additionally desire to convey my appreciation to the staff members within my department who provided me with extra support from the faculty.

I wish to express my deep gratitude to my beloved mother and my spouse who quietly supported me during my time abroad for my doctoral study. Thanks to my dear daughters for their efforts so that they can realize their own value of life as I do.

Yadong Liu

หัวข้อดุษฎีนิพนธ์	ความสัมพันธ์ระหว่างบิตคอยน์และสินทรัพย์ทางการเงินแบบดั้งเดิม ในบริบทของการตัดสินใจซื้อขาย: แนวทาง DCC-GARCH พร้อมกับการเรียนรู้ของเครื่อง
ผู้เขียน	นายหยาตง หลิว
ปริญญา	ปรัชญาดุษฎีบัณฑิต (นวัตกรรมดิจิทัลและเทคโนโลยีการเงิน)
คณะกรรมการที่ปรึกษา	อาจารย์ ดร.นที นาคธนสุกาญจน์ อาจารย์ที่ปรึกษาหลัก อาจารย์ ดร.อนุกูล แต้มประเสริฐ อาจารย์ที่ปรึกษาร่วม อาจารย์ ดร.ธนารัตน์ รัตนดำรงอักษร อาจารย์ที่ปรึกษาร่วม

บทคัดย่อ

เศรษฐกิจทุกวันนี้ต้องการธุรกรรมที่รวดเร็ว ราคาไม่แพง และเชื่อถือได้ บิตคอยน์ (BTC) ซึ่งเป็นสกุลเงินดิจิทัลที่สร้างโดย Satoshi Nakamoto ในปี 2008 เป็นหนึ่งในเครื่องมือที่เป็นนวัตกรรมใหม่สำหรับการทำธุรกรรมและการชำระเงิน BTC ซึ่งเป็นหนึ่งในสกุลเงินดิจิทัลแรกสุดที่ค้นพบนั้น มีพื้นฐานอยู่บนเครือข่ายแบบกระจายอำนาจ ที่อนุญาตให้ทำธุรกรรมแบบ peer-to-peer ที่เป็นส่วนตัว และไม่เปิดเผยตัวตน ได้ทุกที่ ในทางกลับกัน ปัญหาการทำนายราคาและการลงทุน มีความสำคัญสำหรับทั้งนักวิเคราะห์ทางการเงินและเทรดเดอร์ นอกจากนี้ ในช่วงไม่กี่ปีที่ผ่านมา วิธีการเรียนรู้ของเครื่องจักรได้ถูกพบว่ามีการใช้งานอย่างมากมายในการคาดการณ์แบบอนุกรมเวลา ดังนั้น ในการศึกษานี้ เป็นครั้งแรกที่มีการเสนอและประยุกต์วิธีเครือข่ายประสาทเทียม Dynamic Conditional Correlation - Generalized Autoregressive Conditional Heteroscedasticity กับการตัดสินใจลงทุนของ BTC ในทางกลับกัน ผู้กำหนดนโยบาย นายธนาคารกลาง ผู้จัดการพอร์ตโฟลิโอ นักลงทุน และ เทรดเดอร์จำเป็นต้องค้นหาความสัมพันธ์กับ โลหะมีค่า น้ำมัน และดอลลาร์สหรัฐในการคาดการณ์การลงทุนใน BTC อย่างไรก็ตาม วรรณกรรมที่มีอยู่มากมายเป็นการตรวจสอบความสัมพันธ์ระหว่าง BTC และแนวปฏิบัติดั้งเดิม

การศึกษานี้ ตรวจสอบความสัมพันธ์ระยะยาวที่ไม่สมมาตร สาเหตุที่ไม่สมมาตร และความสัมพันธ์แบบพลวัต ระหว่างทองคำ น้ำมันดิบ และดอลลาร์สหรัฐ เมื่อพิจารณาปัจจัยเหล่านี้ จึงมีคำถามต่อไปนี้เสนอในบทความนี้ (1) มีความสัมพันธ์ระยะยาวที่ไม่สมมาตรหรือไม่ ระหว่าง BTC กับสินทรัพย์การลงทุนแบบดั้งเดิม เช่น ทองคำ น้ำมันดิบ และดอลลาร์สหรัฐ (2) มีสาเหตุที่ไม่

สมมาตรหรือไม่ ระหว่าง BTC และสินทรัพย์การลงทุนแบบดั้งเดิม เช่น ทองคำ น้ำมันดิบ และดอลลาร์สหรัฐ (3) มีความสัมพันธ์แบบพลวัตหรือไม่ ระหว่าง BTC กับสินทรัพย์การลงทุนแบบดั้งเดิม เช่น ทองคำ น้ำมันดิบ และดอลลาร์สหรัฐ (4) ทฤษฎีเศรษฐศาสตร์ข้อใดที่รองรับการคาดการณ์การลงทุน BTC (5) โมเดล ANN-DCC-GARCH ดีเพียงพอสำหรับการคาดการณ์การลงทุน BTC หรือไม่ เพื่อตอบคำถามการวิจัยเหล่านี้ เอกสารงานวิจัยนี้จะตรวจสอบความสัมพันธ์ระหว่าง BTC กับสินทรัพย์การลงทุนแบบดั้งเดิมอย่าง ทองคำ น้ำมันดิบ และดอลลาร์สหรัฐ และในขณะเดียวกันก็เสนอโมเดลรูปแบบใหม่ สำหรับการตัดสินใจลงทุน BTC เพื่อวิเคราะห์และตอบคำถามเชิงประจักษ์

การวิเคราะห์เชิงประจักษ์ประกอบด้วยสามส่วน: ในส่วนแรก เลือกข้อมูลของ BTC, ทองคำ, น้ำมันดิบ และดัชนีดอลลาร์สหรัฐ จาก Yahoo Finance ข้อมูลรายสัปดาห์ตั้งแต่วันที่ 1 มกราคม 2015 ถึงวันที่ 15 มิถุนายน 2023 จะได้รับการวิเคราะห์ และใช้วิธีการตรวจสอบความสัมพันธ์ระยะยาวที่ไม่สมมาตร และทดสอบสาเหตุที่ไม่สมมาตร ข้อสรุปเชิงประจักษ์แสดงให้เห็นว่าไม่มีความสัมพันธ์ระยะยาวในความหมายดั้งเดิม ระหว่าง BTC และสินทรัพย์ทางการเงินแบบดั้งเดิม แต่มีความสัมพันธ์ระยะยาวที่ไม่สมมาตร มีความสัมพันธ์ระยะยาวระหว่างการเพิ่มขึ้นของ BTC และการลดลงของดัชนีดอลลาร์สหรัฐ และ มีความสัมพันธ์ระยะยาวระหว่างการลดลงของ BTC และการเพิ่มขึ้นและการลดลงของสินทรัพย์ทางการเงินแบบดั้งเดิมทั้งสามรายการ น้ำมันดิบมีความสัมพันธ์เป็นเหตุและผลแบบ Granger Causality สำหรับ BTC ในขณะที่ทองคำและดอลลาร์สหรัฐไม่ใช่ ก่อนเกิดโรคระบาดโควิด-19 การลดลงของราคาทองคำมีความสัมพันธ์เป็นเหตุและผลแบบ Granger Causality สำหรับการเพิ่มขึ้นของราคา BTC แต่หลังจากการแพร่ระบาดของโรคระบาดโควิด-19 ราคาน้ำมันดิบที่ลดลงมีความสัมพันธ์เป็นเหตุและผลแบบ Granger Causality สำหรับการลดลงของราคา BTC การแพร่ระบาดของโควิด-19 นำไปสู่การเปลี่ยนแปลงในความสัมพันธ์เป็นเหตุและผล ระหว่าง BTC และสินทรัพย์ทางการเงินแบบดั้งเดิม อย่างไรก็ตาม เงินดอลลาร์สหรัฐไม่มีความสัมพันธ์เป็นเหตุและผลแบบ Granger Causality กับการเปลี่ยนแปลงราคา BTC

ในส่วนที่สอง เราเลือกข้อมูลรายสัปดาห์ตั้งแต่เดือนมกราคม 2014 ถึงเมษายน 2022 และวัดความสัมพันธ์ระหว่าง BTC กับน้ำมันดิบ และ BTC กับทองคำ โดยใช้แบบจำลอง DCC-GARCH ผลการทดลองแสดงให้เห็นว่า (1) BTC มีความเสี่ยงมากกว่าทองคำ และน้ำมันดิบ ขณะที่ทองคำ มีความเสี่ยงต่ำที่สุด อย่างไรก็ตาม น้ำมันดิบมีความเสี่ยงมากกว่าในช่วงแรกของการแพร่ระบาดของไวรัสโควิด-19 (2) ผลตอบแทนของ BTC มีความสัมพันธ์เชิงลบกับความเสี่ยง ในขณะที่ผลตอบแทนของทองคำและน้ำมันดิบ ไม่มีความสัมพันธ์อย่างมีนัยสำคัญกับความเสี่ยง (3) ความสัมพันธ์ระหว่าง BTC กับน้ำมันดิบ และระหว่าง BTC กับทองคำ แสดงให้เห็นถึงความผันผวนอย่างมีนัยสำคัญ เราเห็นการเพิ่มขึ้นของความสัมพันธ์เชิงบวกระหว่าง BTC กับน้ำมันดิบ ในช่วงเริ่มต้นของการแพร่ระบาดของโค

วิด-19 ในทางตรงกันข้าม ความสัมพันธ์เชิงลบระหว่าง BTC และทองคำ มีความชัดเจนมากขึ้นในช่วงเริ่มต้นของการแพร่ระบาดของโควิด-19

ในส่วนที่สามของบทความนี้ มีการเสนอและประยุกต์วิธีเครือข่ายประสาทเทียม DCC-GARCH กับการตัดสินใจลงทุนของ BTC ซึ่งให้ข้อมูลในอดีตเกี่ยวกับความสัมพันธ์และความแปรปรวนร่วมของ BTC กับสินทรัพย์ทางการเงินแบบดั้งเดิม ข้อมูลได้มาจาก ฐานข้อมูล Wind ข้อมูลเป็นรายวัน และระยะเวลาตัวอย่างคือตั้งแต่วันที่ 17 กันยายน 2014 ถึง 23 ธันวาคม 2022 ตัวแปรขาเข้าประกอบด้วยราคาสูงสุด ต่ำสุด และราคาเปิดรายวันของ BTC และตัวแปรไบนารี่สำหรับทองคำ ดอลลาร์สหรัฐ และน้ำมันดิบ โดย 0 หมายถึง ราคาลดลง และ 1 หมายถึง ราคาเพิ่มขึ้น ตัวแปรขาเข้าทั้งหมดล่าช้าหนึ่งช่วงเวลา ตัวแปรทั้งหมดถูกทำให้เป็นปกติโดยใช้น้ำหนักเอนโทรปี ยกเว้นตัวแปรไบนารี่ ข้อมูลปี 2019 ถือว่าไม่อยู่ในกลุ่มตัวอย่าง (ก่อนโควิด -19 การระบาด) และข้อมูลปี 2022 ไม่อยู่ในกลุ่มตัวอย่าง (หลังการระบาดของโควิด-19) แต่ละช่วงแบ่งข้อมูลออกเป็นชุดฝึกอบรมและชุดพยากรณ์ ตามลำดับ ชุดฝึกอบรมใช้ค้นหาแบบจำลอง ANN-DCC-GARCH ที่ให้ความแม่นยำในการทำนายที่ดีที่สุด และชุดการคาดการณ์จะใช้ทดสอบประสิทธิภาพของการตัดสินใจลงทุน BTC ผลเชิงประจักษ์พบว่าโมเดล ANN-DCC-GARCH มีผลตอบแทนสะสม 318% ในปี 2019 และสามารถลดการขาดทุนได้ 50% ในปี 2022 ดังนั้น ข้อมูลในอดีต เช่น ความสัมพันธ์ ความผันผวน และความแปรปรวนร่วมระหว่าง BTC และสินทรัพย์ทางการเงินแบบเดิม จึงมีประโยชน์เป็นคำแนะนำในการปรับปรุงธุรกรรมการลงทุนใน BTC นอกจากนี้ การค้นพบโดยรวมยังชี้ให้เห็นว่าแบบจำลอง ANN-DCC-GARCH ทำงานได้ดีสำหรับการตัดสินใจลงทุนใน BTC แต่เราต้องพิจารณาว่าแบบจำลองนี้สามารถทำนายสินทรัพย์ทางการเงินอื่น ๆ ได้ดีเพียงใด การวิจัยในอนาคตของเราสามารถสำรวจการประยุกต์ใช้แบบจำลอง ANN-DCC-GARCH ในพอร์ตการลงทุนสินทรัพย์ทางการเงินที่หลากหลายและวิเคราะห์ผลการคาดการณ์ของแบบจำลองนี้ ต่อธุรกรรมการลงทุนในสินทรัพย์ทางการเงินอื่น ๆ เพิ่มเติม

ด้วยการพัฒนาของเศรษฐกิจตลาด การเกิดขึ้นของสกุลเงินดิจิทัลโดยเฉพาะบิตคอยน์ ได้ดึงดูดความสนใจจากนักลงทุนจำนวนมาก และทำให้มูลค่าของการลงทุนเพิ่มขึ้น สำหรับนักลงทุน วิธีการพัฒนากลยุทธ์การลงทุนสำหรับบิตคอยน์ ได้กลายเป็นความสนใจของนักลงทุน สำหรับกลยุทธ์การลงทุน เป้าหมายการวิจัยที่สำคัญของเศรษฐศาสตร์มหภาคและเศรษฐมิติ คือการทดสอบสมมติฐานและประมาณความสัมพันธ์ระหว่างตัวแปรทางเศรษฐกิจตามทฤษฎีเศรษฐศาสตร์ อย่างไรก็ตาม สำหรับข้อมูลอนุกรมเวลาที่ไม่คงที่ เนื่องจากการทดสอบแบบเดิมใช้ไม่ได้ ด้วยเหตุนี้ จึงไม่สามารถวิเคราะห์ได้เลยหรือสรุปผลผิดโดยสิ้นเชิง ในบทความงานวิจัยนี้ ภายใต้แนวคิดการรวมโมเดลทางเศรษฐมิติและเทคโนโลยีการเรียนรู้ของเครื่องเข้าด้วยกัน เราจึงเสนอโมเดล ANN-DCC-

GARCH เพื่อนำไปใช้ในการตัดสินใจทำธุรกรรมการลงทุนของบิตคอยน์เป็นครั้งแรก เราพบว่านักวิชาการจำนวนไม่มากมุ่งเน้นไปที่ความสัมพันธ์เชิงเป็นเหตุเป็นผล ระหว่างบิตคอยน์กับดอลลาร์สหรัฐ หรือน้ำมันดิบเท่านั้น และไม่ได้ตรวจสอบความสัมพันธ์เชิงเป็นเหตุเป็นผลที่ไม่สมมาตรระหว่างบิตคอยน์และสินทรัพย์ทางการเงินแบบดั้งเดิมอย่างครอบคลุม ดังนั้น จึงเป็นเหตุแห่งความจำเป็นในการศึกษาความแปรปรวนร่วมที่ไม่สมมาตร และสาเหตุที่ไม่สมมาตร ระหว่างบิตคอยน์ และสินทรัพย์ทางการเงินแบบดั้งเดิม เช่น ทองคำ น้ำมันดิบ และดอลลาร์สหรัฐในบทความนี้ เช่นเดียวกับการคาดการณ์การลงทุนและกลยุทธ์การซื้อขายบิตคอยน์ ในช่วงเวลาก่อนและหลังการระบาดของโควิด-19 ตามลำดับ ผลการทำนายของบิตคอยน์ แสดงให้เห็นว่าโมเดล ANN-DCC-GARCH มีการใช้งานได้จริงและใช้งานได้ดี ทั้งยังยืนยันว่าโมเดล ANN-DCC-GARCH นั้นเหนือกว่า ANN โดยสิ้นเชิง นักวิชาการหลายคนใช้โมเดล DCC-GARCH เพื่อวิเคราะห์ความสัมพันธ์แบบพลวัต และความผันผวนของสินทรัพย์ทางการเงินแบบดั้งเดิม และให้คำแนะนำการลงทุนโดยอิงจากข้อสรุปของความสัมพันธ์แบบพลวัตและความผันผวน ดังนั้น การวิจัยในอนาคตของเราจึงสามารถสำรวจการประยุกต์ใช้แบบจำลอง ANN-DCC-GARCH ในพอร์ตการลงทุนสินทรัพย์ทางการเงินที่หลากหลาย และวิเคราะห์ผลการคาดการณ์ของแบบจำลองต่อธุรกรรมการลงทุนในสินทรัพย์ทางการเงินอื่น ๆ เพิ่มเติมต่อไป

Dissertation Title The Relationship Between Bitcoin and Traditional Financial Assets in The Context of Trading Decisions: A DCC-GARCH Approach with Machine Learning

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Degree Doctor of Philosophy (Digital Innovation and Financial Technology)

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ABSTRACT

Today's economy requires fast, inexpensive, and reliable transactions. Bitcoin (BTC), the cryptocurrency constructed by Satoshi Nakamoto in 2008, is one of the innovative tools used for transactions and payments. BTC, one of the earliest cryptocurrencies discovered, is based on a decentralized network that allows private, anonymous user-to-user transactions anywhere. On the contrary, price prediction problems and investments are significant for both financial analysts and traders. Moreover, in the past few years, machine learning methods have found many applications in time series forecasting. Therefore, in this study, for the first time, a Dynamic Conditional Correlation - Generalized Autoregressive Conditional Heteroscedasticity artificial neural network method is proposed and applied to the investment decision of BTC. On the other hand, policymakers, central bankers, portfolio managers, investors, and traders need to find the correlations with precious metal, petroleum, and the American currency in BTC investment forecasts. However, much-existing literature examines the correlation between BTC and conventional practices.

Based on economic theory, this study examines the asymmetric cointegration, asymmetric causality, and vibrant connection among gold, petroleum, and the American dollar. Considering these factors, the following questions are proposed in this article. (1) Is there an asymmetric cointegration relationship between BTC and traditional investment assets, i.e., Gold, crude Oil, and the U.S. dollar? (2) Is there an asymmetric causality between BTC and traditional investment assets, i.e., Gold, crude Oil, and the U.S. dollar? (3) Is there a dynamic correlation between BTC and traditional investment assets, i.e., Gold, crude Oil? (4) What economic theory underlies the BTC investment forecasts? (5) Is the ANN-DCC-GARCH model good enough for BTC investment decisions? To answer the research questions, this paper separately examines the correlation between BTC and the traditional investment asset ie. Gold, oil, US dollars. At the same time, we propose a new model for BTC investment decisions to analyze and answer the posed questions empirically.

The empirical analysis involves three parts: in the first part, we selected the data of BTC, gold, crude oil, and dollar index from Yahoo Finance. Weekly data from January 1, 2015, to June 15, 2023, are analyzed, and the methodology uses asymmetric cointegration and asymmetric causality tests. The empirical conclusions show no cointegration in the traditional sense between BTC and traditional financial assets, but there is an asymmetric cointegration instead. There is a cointegrating correlation between the increase of BTC and the decrease in the U.S. dollar index and between the decline of BTC and the growth and reduction of all three financial assets. Crude oil is a Granger causality for BTC; while gold and US dollar are not. Before the epidemic, the fall of gold was the Granger causality for the rise of BTC. Following the COVID-19 pandemic, the drop in crude oil price was the Granger causality for the decline in BTC price. The COVID-19 outbreak altered the causal connection between BTC and traditional financial assets. However, the US dollar did not cause a shift in BTC price.

In the latter section, we opt for data on a weekly basis, covering the period from January 2014 to April 2022, and assess the fluctuating correlation between BTC and crude oil, or BTC and gold, using the DCC-GARCH model. The empirical results show that (1) BTC is riskier than gold and crude oil, while gold has the lowest risk. However, crude oil is more dangerous in the early stages of the COVID-19 epidemic. (2) Returns on BTC are negatively correlated with risk, while returns on gold and crude oil are not significantly correlated with risk. (3) The relationship between BTC and crude oil, as well as BTC and gold, demonstrates noteworthy volatility. We observe a notable rise in the positive correlation between BTC and crude oil during the initial stages of the COVID-19 pandemic. Conversely, the opposite relationship between BTC and gold became more noticeable at the beginning of the COVID-19 pandemic.

In the third part of this paper, a DCC-GARCH artificial neural network method is proposed and applied to the investment decision of BTC, which provides historical information on the correlation and covariance of BTC with traditional financial assets. The information is sourced from the Wind database. The dataset comprises of daily observations, spanning from September 17, 2014, to December 23, 2022. The input variables encompass the highest daily values, low, and opening prices of BTC and binary variables for gold, the US dollar, and crude oil. 0 represents a price decline, and 1 represents a price increase. All input variables are lagged in one period. All variables are normalized using entropy weights except for the binary variables. The 2019 data are considered out-of-sample before the COVID-19 outbreak, and the 2022 data are out-of-sample after the COVID-19 outbreak. Each timeframe is segmented into a training subset and a forecasting subset correspondingly. The training subset is employed to establish the ANN-DCC-GARCH model that yields the most accurate prediction, and the prediction set is used to test the performance of BTC investment decisions. The practical findings demonstrate that the ANN-DCC-GARCH model has a cumulative return of 318% in 2019 and can reduce the loss by 50% in 2022. Therefore, historical information such as correlation, volatility, and covariance between BTC and traditional financial assets is indeed instructive for improving investment transactions in BTC. In addition, the overall findings suggest that the ANN-DCC-GARCH model works well for BTC investment decisions, but we need to figure out how well the model predicts other financial assets. Our future research can explore the application of the ANN-DCC-GARCH model in diversified financial asset portfolios and further analyze the model's predictive effect on investment transactions in other financial assets.

As the market economy has advanced, the rise of digital currencies, notably BTC, has drawn considerable interest from investors, leading to increased scrutiny of its investment worth. For investors how to develop an investment strategy for BTC has become a concern for investors. For investment strategies, an important research goal of macroeconomics and econometrics is to test hypotheses and estimate the relationship between economic variables based on economic theory. However, for non-stationary time series, since the traditional tests are no longer valid, one either cannot analyze them at all or can draw completely wrong conclusions. In this paper, under the concept of combining econometric and machine learning models, we propose the ANN-DCC-GARCH model and apply it for the first time to the investment transaction decision of BTC. It is found that a small number of scholars only focus on the causal relationship between Bitcoin and US dollar or crude oil, and do not comprehensively determine the asymmetric causal relationship between BTC and traditional financial assets. Hence, it is imperative to examine the non-symmetric covariance and non-symmetric causal relations between BTC and conventional financial assets, specifically gold, crude oil, and the US dollar in this paper, as well as predicting BTC investment and trading strategies before and after the outbreak of COVID-19 respectively. The prediction results of BTC show that the ANN-DCC-GARCH model has good practicality and operability, and also verify that the ANN-DCC-GARCH model is completely superior to the ANN model. Many scholars use the DCC-GARCH model to analyze the dynamic correlation and volatility of traditional financial assets and give investment recommendations based on the conclusions of dynamic correlation and volatility. Therefore, our future research can explore the application of the ANN-DCC-GARCH model in diversified financial asset portfolios and further analyze the model's predictive effect on investment transactions in other financial assets.

Keywords: Cryptocurrency, BTC, COVID-19, crude oil, gold, ANN-DCC-GARCH

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LIST OF ABBREVIATION

BTC	Bitcon
DCC	Dynamic Conditional Corelational
COVID-19	Coronavirus Disease 2019
GARCH	Autoregressive Conditional Heteroscedasticity
ANN	Artifical Neural Network
ARCH	Autoregressive Conditional Heteroskedasticity
KNN	K-Nearest Neighbors Algorithm
DLT	Distributed Ledger Technology t
SDR	Special Drawing Rights
IMF	International Monetary Fund
CBDC	Central Bank Digital Currency
GES	Gold Exchange Standard
ECB	The European Central Bank
IMF	Morgan Stanley Capital International
BIS	Bank for International Settlements
EBA	The European Banking Authority
ESMA	The European Securities and Markets Authority
FATF	The Financial Action Task Force
MMT	Modern Monetary Theory
ATM	Automated Teller Machine
BCH	BTC Cash
BCD	BTC Diamond
BTG	BTC Gold
ZKP	Zero-Knowledge Proof
MPT	Modern Portfolio Theory
VAR	Vector Autoregression Mode
ECM	Error Correction Model
STVAR	Spatial and Temporal Vector Autoregressive
BEKK	Baba, Engle, Kraft, and Kroner - Generalized

S&P	Standard & Poors
E-GARCH	Exponential GARCH
GBM	Gradient Boosting Machines
DOW	Dow Jones Industrial Average
NASDAQ	National Association of Securities Dealers Automated Quotations
OLS	Ordinary Least Squares
QR	Quartile Regression
AR	Univariate Autoregression
ARIMA	Autoregressive Integrated Moving Average
LSTM	Long Short-Term Memory
SES	Simple Exponential Smoothing
ARMA	Autoregressive Moving Average
SDAE	Stacked Denoising Autoencoder
DFA	Detrended Fluctuation Analysis
MSGARCH	Multivariate Fractionally Integrated-GARCH
FCVAR	Factor-Corrected VAR
MF-DCCA	Multifractal Detrended Cross-Correlation Analysis
MIDAS	Mixed Data Sampling
NARX	Nonlinear AutoRegressive model with eXogenous inputs
VEC	Vector Error Correction
FCVAR	Fractionally Cointegrated VAR Model
PLR	Probabilistic Logistic Regression
WSVM	Weighted Support Vector Machines
ADF	Augmented Dickey-Fuller
ANFIS	Adaptive Neuro-Fuzzy Inference System
GARP	Global Association of Risk Professionals
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
PP	Phillips-Perron
BP	Back Propagation
XOR	Exclusive OR
USDX	US Dollar Index Futures

NYSE	The New York Stock Exchange
WTI	West Texas Intermediate
CBDC	Central Bank Digital Currency

ข้อความแห่งการริเริ่ม

ผู้วิจัยขอรับรองว่าวิทยานิพนธ์เล่มนี้มิได้ละเมิดลิขสิทธิ์ของผู้ใด รวมถึงมิได้ขัดต่อสิทธิ์ในการเป็นเจ้าของทรัพย์สินใดๆ และขอรับรองด้วยว่าแนวคิด เทคนิค คำกล่าว หรือเนื้อหาอื่นใดจากงานของผู้อื่นที่ได้รวมอยู่ในวิทยานิพนธ์เล่มนี้ ได้รับการยอมรับอย่างครบถ้วนโดยทั่วกันตามหลักมาตรฐานการอ้างอิงแล้ว ผู้วิจัยขอแจ้งว่าเอกสารเล่มนี้เป็นสำเนาถูกต้องของวิทยานิพนธ์ของผู้วิจัย ซึ่งรวมไปถึงการแก้ไขปรับปรุงล่าสุดตามที่ถูกรับรองจากคณะกรรมการสอบวิทยานิพนธ์และบัณฑิตวิทยาลัย และขอแจ้งด้วยว่าวิทยานิพนธ์นี้มิเคยถูกนำเสนอเพื่อการสำเร็จการศึกษาจากมหาวิทยาลัยหรือสถาบันใดมาก่อน

STATEMENT OF ORIGINALITY

This document solemnly affirms that, based on my full assessment, the content of my paper does not violate any copyright or proprietary rights, and that all ideas, approaches, citations, or external works not originating from my own research featured in the paper have been dutifully and explicitly annotated in accordance with referencing guidelines. Moreover, I hereby assert that the content of this dissertation wholly represents my research, encompassing all modifications ultimately approved by my academic committee and the Graduate School. Furthermore, I verify that this dissertation has never been presented for another academic qualification at any other establishment or college.

CHAPTER 1

INTRODUCTION

Since 2009, the world's financial payment system has faced cryptocurrencies that can only be supported by solving complex mathematical equations. Due to the ease of international transfers, low operating costs, and the absence of intermediaries and regulators, such currencies quickly took their place in the monetary and financial systems of various countries. For example, the best-known cryptocurrency, BTC, has risen from less than $1 to more than $1,000 quickly. BTC is used as a payment method by many companies, and the issue of its investment decisions and price predictions is fond of many researchers, investors, and decision-makers. Investors want to understand future price prediction strategies for buying or selling cryptocurrencies. Policymakers want to understand the various aspects of BTC and the metrics that may affect its value in order to shape future decisions of BTC in countries' financial systems. To determine if there is a relationship between investments in BTC including the customary financial instruments of Gold, Oil, and the U.S. currency. Whether correlations between conventional financial assets inform investment decisions in BTC. Hence, it is essential to understand the relationship between BTC and established financial assets, including Gold, Oil, and the U.S. dollar, for investment decisions in BTC, as it is an emerging valuable topic for future economic development. This chapter provides an overview and outlines the importance of the study, research questions and hypotheses, research methodology, and content. This chapter first introduces the background and current status of the research for BTC investment, and what are the relationships with the traditional financial instruments such as Gold, Crude Oil, and the American dollar. It explains the object, problem and current status of the current article's research, and clarifies the framework of the article's research.

1.1 Research Background

This section addresses the background of this study, providing an overview of the correlation between BTC and traditional financial instruments like Gold, Oil, and the U.S. dollar including static correlations such as asymmetric cointegration and asymmetric causality, dynamic correlations, volatility, BTC investment trading decisions, and prediction methods such as qualitative prediction methods, quantitative prediction methods, neural network methods, and machine learning methods. Finally, it is clarified why this research is needed, and the current research is presented as further academic knowledge.

As a decentralized digital virtual currency, the concept of BTC was first proposed in 2008. BTC was formally introduced in January 2009 and was the premier cryptographic digital currency in the world (Basher & Sadorsky, 2022). Compared to cryptocurrencies, on the one hand, BTC saves transaction costs (Kayal & Rohilla, 2021) and is independent of central banks (Baur & Dimpfl, 2021). On the other hand, anyone can mine, purchase, exchange, or receive BTCs, and no one can ascertain the user's identity throughout the transaction (Chen, 2023). Perhaps because of this, the BTC market is sought after by financial institutions and investors. Additionally, it is worth noting that BTC is a financial asset characterized by high risk and high potential returns (Baek & Elbeck, 2015; Cheah et al., 2022; Huang et al., 2019). During the COVID-19 pandemic in 2021, the price of BTC surpassed $68,000 per coin. However, by the conclusion of 2022, the BTC price dropped below $20,000 once again. The evident volatility in the BTC price is apparent. This is precisely why numerous speculators and financial institutions express a strong interest in investing in BTC. Speculators are particularly focused on making sound investment decisions or achieving more accurate predictions of the BTC price. which is one of the primary aims of this study.

Figure 1.1 BTC prices from Sept. 2014 to Dec. 2022

Source: (from the Wind database)

Different phases in BTC trading require distinct strategies. In Figure 1.1, the daily closing prices of BTC are depicted from 2014 to 2022. Post the emergence of the COVID-19 pandemic, BTC experienced a bullish trend from 2019 to early 2021, followed by a complete bear market in the latter half of 2021, causing prices to regress to 2020 levels. This underscores BTC's status as a premium investment asset until 2021. Evidently, investors in BTC should employ diverse investment approaches pre and post the pandemic. Notably, BTC investors and financial institutions aim to maximize profits during bull markets and mitigate investment risks during bear markets. Hence, the pertinent questions to be addressed in this study are: How should investors formulate BTC investment strategies in different periods? Can this expectation be met through a forecasting methodology?

Certain academics argue that the decrease in BTC value is impacted by the fluctuations in the price of the U.S. dollar, Gold, Oil, and other factors.(Al-Khazali et al., 2018; Bani-Khalaf & Taspinar, 2023; Dyhrberg, 2016; Grobys, 2021). The U.S. dollar, Gold, and crude Oil are also considered conventional hedging assets. (Wei et al., 2021). Significantly, with the surge in the BTC market, certain researchers have identified BTC as a crucial hedging asset as well (Bouri et al., 2020; Wang et al., 2019). In addition, Corbet et al. (2020) observed that there is a stronger correlation between BTC and traditional financial assets, especially following the onset of the COVID-19 pandemic.

Figure 1.2 depicts the price movements of Gold and BTC from November 24, 2013 to November 24, 2021. As illustrated by figure 1.2, the value trajectory of Gold remains quite steady, whereas the price fluctuations of BTC are significant, indicating that BTC is an asset characterized by high returns, substantial speculative interest, and pronounced volatility.

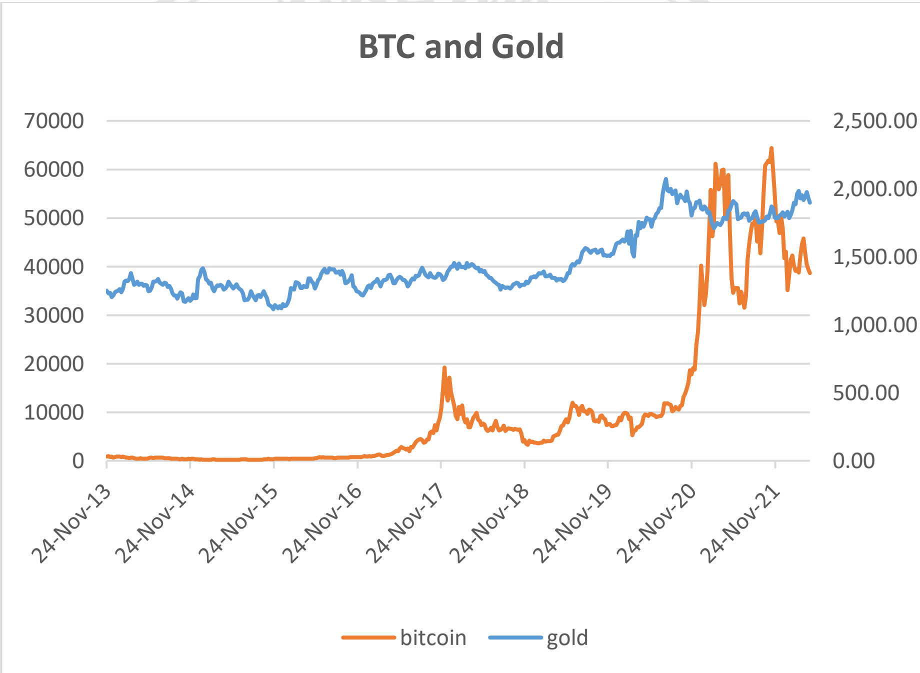

Figure 1.2 The prices of BTC and Gold

As an important commodity market, the crude oil market not only holds a vital position in the functioning of the global economy and foreign trade but is also closely related to the financial market and has become a common financial instrument. On the one hand, investors believe that bulk commodities such as crude Oil have the ability to resist inflation in the long run and can be used to avoid the impact of inflation. However, the market price for crude Oil experiences significant fluctuations, and a "bottom reading" at the right time can obtain speculative profits. In addition, several scholars have discovered a close correlation between the crude Oil market and the Gold market. (Coronado et al., 2018; Y.-J. et al., 2010), and there may be a linkage between the two. Figure 1.3 illustrates the price fluctuations of crude Oil and BTC from November 24, 2013 to November 24, 2021. The price change trend of the two shows that the fluctuation of crude Oil market price is more obvious, and there is a notable decline beginning on November 24, 2013 to April 19, 2020, and the price rises from April 20, 2020 to November 24, 2021. Building on the preceding analysis, the volatility in the crude Oil market, BTC market, and Gold market has successively diminished. There is a heightened connection between BTC and traditional financial assets, especially post the advent of the Covid-19 pandemic. It is widely acknowledged that the more comprehensive our understanding of information, the more advantageous it is for our investment choices. Given the discernible relationships between BTC and traditional financial assets, is it advantageous to inform BTC investment decisions by elucidating these associations? This holds significant implications for the majority of BTC investors.

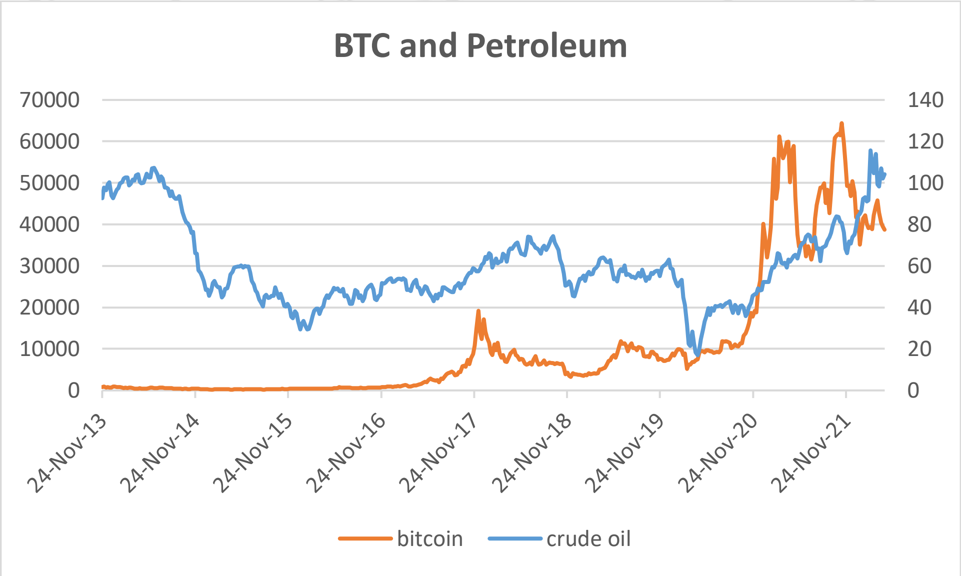

Figure 1.3 The prices of BTC and petroleum

Chen and Kung (1984) predictive methods can be widely classified as qualitative and quantitative methods, depending on how mathematical and statistical methods are used. Qualitative forecasting methods include mental estimation through expert opinions, usually used when past data are not available or scarce and unavailable. Qualitative forecasting methods can be done using judgment, direct understanding, business knowledge, and other appropriate information (Chambers et al., 1971). Some qualitative forecasting methods are the Delphi technique, market analysis, and historical life-cycle comparison. Moreover, there are two main types of quantitative methods: structural models and time series models. Traditional economic modeling has explained the relationships between economic variables and economic units' rational behavior, including producers, consumers, and financial policymakers. Economists estimate the relationships using various econometric methods, explain the existing situation, predict the dependent variables, and establish economic policies. The described models, typically called structural models, have been used analytically as appropriate economic policymaking tools; however, it is not very successful in forecasting. The existence of this critical shortcoming, and on the other hand, the growing importance of forecasting for government policymakers and private sector policymakers, gradually provided new conditions and perspectives for prediction modeling.

Recently, another perspective has been introduced in the applied economics literature. Utilizing artificial intelligence to comprehend the connections among variables is feasible, even if they are complex, and predict future values. This view, which is, in fact, an adaptation of the human brain learning process (natural intelligence), was first used in other areas such as physics, computers, and engineering and had very successful results. Due to these techniques' unparalleled success in predicting economic variables, they are often used to forecast problems. Economists have been using these models since the mid-1990s, typically known as machine learning models (Rudin, 2019). According to this view, if the existing relationships between economic variables can be learned by a computer using information search methods, they can also predict future values.

In recent years, numerous scholars have undertaken direct studies focused on predicting BTC. (Adcock & Gradojevic, 2019; Atsalakis et al., 2019; Hau et al., 2021; Pabuçcu et al., 2023; Tripathi & Sharma, 2022; Wang & Hausken, 2022). Huang and Gao (2022) employed the LASSO methodology for forecasting BTC returns during the period from 2018 to 2019 J.-N. Wang et al. (2019) utilized the autoregressive jump intensity (ARJI) model to anticipate the volatility of BTC in 2018.

El Akraoui and Daoui (2022) employed artificial neural networks to evaluate trading approaches using high-frequency BTC price data. Adcock and Gradojevic (2019) utilized feedforward neural networks for forecasting BTC prices. Pabuçcu et al.(2023) used Support Vector Machines (SVM), Artificial Neural Networks (ANN), the Naive Bayes (N.B.), Random Forest (R.F.), and performing logit regression to forecast BTC prices. The majority of research indicates that machine learning approaches outperform time series models in forecasting BTC.

This research has important implications for international finance and machine learning methods. International finance has been part of the developing economy in one way or another for the past few centuries. As the world economy becomes increasingly digitized, international financial payments need to be safer, faster and easier. Today, technology is once again bringing disruptive mechanisms that disrupt existing methods and create a smoother, frictionless, and more cost-effective way of transacting both domestically and internationally. BTC and the cryptocurrency market as a whole have challenged the traditional methods and brought about a more transparent and less dependent mechanism to assist in international financial transactions. During the nascent phase of cryptocurrencies and are expected to take more time to properly stabilize their volatility and make them a beneficial factor in international finance, they do have the elements to prove their capabilities. Since the development of cryptocurrencies is not under the control of any government or authority, it is important to have enough knowledge to help policymakers make better strategic decisions to control the future of cryptocurrencies. Such special periods, such as before and after Covid-19, have a good impact on BTC investments. Moreover, due to the uniqueness of cryptocurrencies, many international online stores such as eBay, Amazon, and the App Store are using cryptocurrencies for payment (Hashemi Joo et al., 2020), which indicates that cryptocurrencies are growing in importance. Therefore, investigation into the dynamics of cryptocurrencies is necessary, especially the aspects of cryptocurrencies represented by BTC. Conversely, the domain of machine learning is proliferating across numerous sectors, including financial time series forecasting. While traditional forecasting algorithms only consider linear relationships between variables, emerging machine learning methods can identify nonlinear relationships between features and dependent variables. This study aims to utilize the emerging methods in the discipline of computing to provide a better reference for the financial industry, especially for investors.

1.2 Problem Statement

Certain researchers have endeavored to forecast the price fluctuations of BTC by examining the correlation between BTC and other financial assets, aiming to provide insights for BTC investment (Al Mamun et al., 2020; Erdas & Caglar, 2018; Okorie & Lin, 2020). For example, Baur and Hoang (2021) assessed the correlation between BTC and Gold and deduced that a substitution or catch-up phenomenon exists between BTC and Gold. Investors have the opportunity to trade Gold for BTC and acquire BTC to synchronize with the market share of Gold.

Ozturk (2020a) investigated the changing dynamics in the correlation among BTC, crude oil, and Gold. and contended that investors can gain from a portfolio containing these three assets over the long term. (Selmi et al., 2018) demonstrated that BTC could function as both a hedge and a diversifying factor for Oil price fluctuations. (J. H. Kwon, 2020) found a negative correlation between BTC and the dollar and figured out that BTC can be a hedge of the dollar. We can see that evolving conditional correlation-generalized autoregressive conditional heteroscedasticity (DCC-GARCH) models are frequently used to evaluate changing correlations over time.

In the contemporary era, numerous researchers have directly engaged in forecast studies on BTC, and Engle et al. (1987) proposed the concept of autoregressive conditional model (ARCH). It is a new method arising from the improvement of the traditional linear or nonlinear time series analysis theory, which has a better fitting effect and forecasting ability and is widely used in the fields of finance insurance, etc. June 10, 2021, Venter and Maré (2021) applied single-variable and multi-variable GARCH models in the valuation of BTC futures options, comparing the model price with the market price to show the pricing performance and also suggested a multi-dimensional BTC futures option pricing approach relying on multi-dimensional GARCH model, that demonstrated via practical findings that symmetric model is more appropriate when employed on BTC futures returns. Azar et al. (2017) selected all the firms that had been members of the Tehran Stock Exchange from the year 2011 to the end of 2015, applying the loss function and assessed the effectiveness of the portfolio allocation target prediction model using the generalized GARCH method. The GRACH model proved to have its own advantages in the study of time series data.

Akyildirim et al. (2021) employed the logarithmic yield for computing the daily gain, scrutinized the statistical properties of the yields of three digital cryptocurrencies: BTC, Ethereum, and Litecoin, and constructed a GARCH family model for empirical testing on the basis of which to explore the volatility characteristics of the returns of three crypto digital currencies. Uğurlu (2019) combines theoretical methods with practical applications, and carefully explains how the GARCH model operates in Eviews by giving examples. Marshall and Siegel (1996) employs a multi-dimensional GARCH model to illustrate the volatility dynamics of portfolio returns, estimate the value at risk (VAR) to assess portfolio risk, and develops a portfolio selection model based on minimizing the VAR value. Selmi et al. (2018) illustrates the connection between BTC and Gold as well as the price of crude Oil by employing quantile regression analysis, and the findings indicate that Gold and BTC can indeed serve as a protective asset for crude Oil. Junttila et al. (2018) can be utilized as protective assets for crude Oil, and their hedging effectiveness is more apparent during periods of economic upheaval. Shahzad et al. (2019) conducted a practical investigation into the correlation among BTC, Gold, and commodities, along with the stock market, utilizing the Cross-quantilogram methodology, and the results found that in the extreme downturn stage of the economy, BTC, like Gold and commodities, has a certain risk aversion properties. Conversely, Corbet et al. (2018) demonstrate that cryptocurrencies and financial assets are separate entities, i.e., incorporating cryptocurrencies into portfolios can be advantageous for investors (Corbet et al., 2020) while based on the quartile-based Granger causality approach finds bidirectional Granger causality in both tails for BTC, torrents, and traditional financial assets. Finally, as a shelter asset, their performance during phases of increased external economic pressures is important, Fang et al. (2019) Observed that heightened global economic uncertainty amplifies the correlation between BTC and securities, as well as BTC and commodities, suggesting that BTC can serve as a safe-haven asset in specific circumstances. Conversely, Long et al. (2021) conducted a comparative analysis of the influence of uncertainty on Gold and BTC and discover that a rise in uncertainty has a more pronounced effect on Gold than its decrease, although BTC does not show analogous attributes. With the COVID-19 pandemic currently spreading worldwide, a "black swan" event that could have far-reaching consequences for the global economy, Khelifa et al. (2021) evaluate the performance of traditional hedge funds and those incorporating cryptocurrencies in the context of the COVID-19 pandemic. finding that, except hedge funds that incorporate cryptocurrencies, all other hedge funds are affected by the Covid-19, but not all other hedge funds. Cryptocurrency-containing hedge funds, all others experienced a decline in value under the shock. The literature above demonstrates a clear correlation between BTC and conventional financial assets. Many scholars have placed special emphasis on BTC's correlation with financial assets like Gold, oil, and the U.S. dollar, as well as the risk premium associated with them. Many scholars point out that estimating the correlation and the risk premium associated with financial products provides advantages for portfolio and investment decisions. However, there are no quantitative methods to shed light on investment decisions for financial products. Since BTC is correlated with traditional financial assets, the objective of this study is to investigate the presence of a cointegrating relationship, specifically an asymmetric one, between BTC and traditional financial assets such as Gold, crude Oil, and the U.S. dollar. Building upon cointegration analysis, this paper additionally identifies the causal relationship, particularly the asymmetric causal relationship, between BTC and established financial assets. Is it advantageous to inform BTC investment decisions by elucidating these relationships simultaneously? This holds significant relevance for BTC investors. Investigating whether the causal relationship has altered before and after the COVID-19 epidemic outbreak, and whether the investment decision regarding BTC has also changed, is one of the research objectives of this paper.

How to enhance the accuracy of predicting the rise and descent of financial assets, particularly BTC, and its volatility is a pressing issue for many individual investors, institutional investors, and even academics. The financial market is a highly complex dynamic system characterized by high dimensionality, nonlinearity, non-stationarity, and low signal-to-noise ratio. The difficulty of making effective forecasts for such a complex dynamic system can be imagined. The theoretical and practical significance of this topic can be summarized as follows: Mainly, to explore the asymmetric cointegration and asymmetric causality between BTC and conventional financial assets, such as Gold, crude Oil, and the U.S. dollar. Second, employing the DCC-GARCH model to investigate the correlation and volatility forecasting between BTC and conventional financial assets assists in offering decision-making guidance for both institutional and individual investors, as well as regulatory and policy reference for financial regulators to timely and effectively prevent financial risks, which has substantial practical application value. Thirdly, combining econometric models and machine learning methods helps to fit and predict financial time series more effectively, which has advantage that traditional econometric methods do not have. The DCC-GARCH model can offer additional insights, such as volatility, dynamic correlation, and so forth, which helps predict financial assets' rise and fall. Therefore, we add more information about the DCC-GARCH model to ANN or KNN to improve prediction accuracy. Fourth, BTC is viewed as a superior portfolio instrument compared to Gold and crude Oil for investors seeking risk. Consequently, during a global financial crisis, investors might lose faith in conventional assets and shift their focus to BTC. Therefore, BTC, crude Oil, and Gold are good portfolio assets. Fifth, BTC and financial assets may perform differently before and during COVID-19. Depending on the investment diversification, investing in BTC, crude Oil, and Gold using the ANN-based DCC-GARCH method or KNN-based DCC-GARCH method may yield better returns. Finally, the utilization and investigation of machine learning in finance bring about a fundamental change in empirical research from linear to nonlinear approaches, and from emphasizing parameter significance to focusing on model architecture and dynamic characteristics.

1.3 Research Questions

Since 2009, BTC has received increasing attention globally due to massive investments from prominent investors. However, policymakers, investors, and traders need more information about the price of BTC, and how to improve the accuracy of predictions about BTC via the relationship in the price data associated with BTC and traditional financial assets is crucial for the future decisions of central banks, investors, and asset managers. According to the existing literature, there are limited studies investigating the relationship Amidst BTC and customary fiscal instruments such as GOLD and the American currency, and Oil that systematically investigate their correlation. There are even fewer studies that utilize the correlation between them to improve the accuracy of BTC forecasts using correlated models. Considering these factors, this thesis investigates the subsequent research inquiries:

1) Is there a cointegrating relationship, especially an asymmetric one between BTC and established financial instruments including crude Oil, Gold, and the U.S. dollar?

2) Is there a causal relationship, especially an asymmetric one, between BTC and conventional financial instruments such as crude Oil, Gold, and the U.S. dollar?

3) Is there a dynamic correlation between BTC and established financial instruments such as crude Oil, Gold, and the U.S. dollar?

4) What is a better way to predict BTC? How can it be applied to make better investment decisions for BTC, taking into account historical information on correlation and covariance with conventional financial assets?

5) Whether there is a difference in the prediction of BTC transactions prior to and following the onset of the COVID-19 pandemic, employing the ANN-DCC-GARCH model for BTC？

1.4 Objectives of the Study

As the BTC market undergoes swift evolution, an increasing array of literature concerning BTC is emerging. The current body of literature primarily concentrates on the correlation between BTC and global economic trends, the financial attributes of BTC, its potential for risk management, and its influence on traditional markets. Conrad et al. (2018) utilized the GARCH-MIDAS model to separate the extended and brief volatility elements of BTC, highlighting the proximity of BTC volatility to worldwide economic trends. Wang et al. (2022) explored the correlation between BTC and various established financial markets. Stensås et al. (2019) analyzed the risk-mitigating capacity of BTC in relation to the FTSE index and the U.S. dollar, Y. Liu and Naktnasukanjn N., (2022) utilized DCC, ADCC, and go GARCH models to examine the replacement of BTC with Gold in the investment portfolio. The findings demonstrated the potential to substitute Gold with BTC in the portfolio, yielding a superior risk-adjusted yield. Wang et al. (2019) witness a minimal impact of Economic Policy Uncertainty (EPU) on the price fluctuations of BTC. Furthermore, Colon et al. (2021) note that cryptocurrencies exhibit limited potential for hedging resistant to shocks from economic policy uncertainty, particularly in positive economic outlooks. Remarkably, in times of heightened economic policy uncertainty, such as those witnessed amid the COVID-19 pandemic, BTC can serve as a viable substitute for conventional assets and provide risk mitigation against uncertainty shocks (Goodell & Huynh, 2020).

Whether the correlation between BTC and Gold, Oil, and the U.S. dollar can help predict the price trend of BTC is the goal of this research paper, which addresses the following three main objectives:

1) To examine the asymmetric integration and causal connection between BTC and traditional financial instruments and whether the causality between them changed before and after the epidemic.
2) To explore the dynamic correlation between BTC and two prominent financial assets, namely crude oil, gold, and the U.S. dollar.
3) To suggest employing a DCC-GARCH combined with an artificial neural network methodology to enhance investment decision-making for BTC, utilizing historical data on correlation and covariance with traditional financial assets.
4) To compare differences in ANN-DCC-GARCH model predictions for BTC Trading Before and After the COVID-19 Outbreak

1.5 Main Contributions of the Research

The precise contributions of this investigation are outlined as follows:

Initially, this manuscript investigates the correlation between BTC and conventional financial instruments, including GOLD, petroleum, and the American currency. This paper focuses on BTC as the primary subject of investigation. The empirical results reveal the lack of a cointegration link between BTC and traditional financial instruments in the standard interpretation. However, there exists an asymmetrical cointegration association. A cointegrating relationship is present between the upswing of BTC and the reduction of the U.S. dollar index, and there is a cointegrating association between the downturn of BTC, as well as both the increase and decrease of the three financial instruments. Crude Oil is a Granger causality for BTC, but Gold and the dollar are not. Before the Covid-19 outbreak, Gold's decline was the Granger causality of BTC's rise. And after the Covid-19 outbreak, the fall in crude Oil prices was the Granger causation of the fall in BTC prices. The COVID-19 pandemic induced a shift in the causal connection between BTC and conventional financial instruments. However, the American currency has not exhibited Granger causality concerning BTC. The outcomes of this investigation bear substantial implications for the decision-making procedures of investors, corporate leaders, and regulatory authorities.

Second, to acquire additional understanding regarding the correlation between BTC and traditional financial instruments, including GOLD, petroleum, and the American currency. This paper examines the evolving correlation between BTC and two critical financial assets, crude Oil and Gold. The DCC-GARCH framework is utilized to evaluate the evolving correlation between BTC and petroleum, as well as BTC and precious metal assets separately. The empirical results suggest that (1) BTC carries higher risk compared to GOLD and petroleum, while GOLD is the least risky. However, petroleum presents heightened risk at the onset of the COVID-19 pandemic. (2) The returns of BTC display an inverse correlation with risk, whereas the returns of GOLD and petroleum exhibit no significant correlation with risk. (3) The association between BTC and petroleum, as well as BTC and GOLD, demonstrates notable volatility. The robust positive correlation between BTC and petroleum significantly increased during the initial phases of the COVID-19 crisis, conversely, the adverse correlation between BTC and GOLD intensified during the commencement of the COVID-19 outbreak. These findings hold substantial reference significance for risk mitigation, prudent investment, and emergency hedging.

Thirdly, this manuscript introduces the ANN-DCC-GARCH model for the inaugural time and employs it for forecasting investment decisions related to BTC. From the perspective of empirical analysis, we verify the benefits of traditional financial assets for BTC investment transaction decisions, additionally, the ANN-DCC-GARCH model's outperformance in comparison to the ANN model.

Fourth, we compare the differences in BTC investment trading decisions before and after the COVID-19 outbreak. It is found that for different risk preferences, the ANN-DCC-GARCH model predicts significant differences in BTC trading decisions. Risk neutrality is the best choice in a bull market, and risk aversion is the best choice in a bear market.

1.6 Conceptual Framework

Firstly, Figure 1.4 illustrates the fixed correlation of BTC with conventional financial instruments, GOLD, Petroleum, and the American currency before and during the COVID-19 pandemic. Building upon this foundation, the present study employs the DCC-GARCH model to gauge and forecast the dynamic correlation between BTC and traditional financial assets: (1) What is the correlation between BTC and GOLD, and between BTC and petroleum? (2) How significant is the disparity between the correlations in the two periods?

Based on the empirical results of risk volatility and dynamic correlation in the DCC-GRACH model, we further apply the combination of the B.P. neural network and the DCC-GARCH model to enhance the precision of BTC investment. This study focuses on predicting the specific relationship between BTC and traditional financial assets in two specific periods, which mainly answers the following questions:(1) How to improve the accuracy of the prediction strategy through the relationship between Bitcoin and traditional financial assets? (2) What is the difference in profits between the two periods?

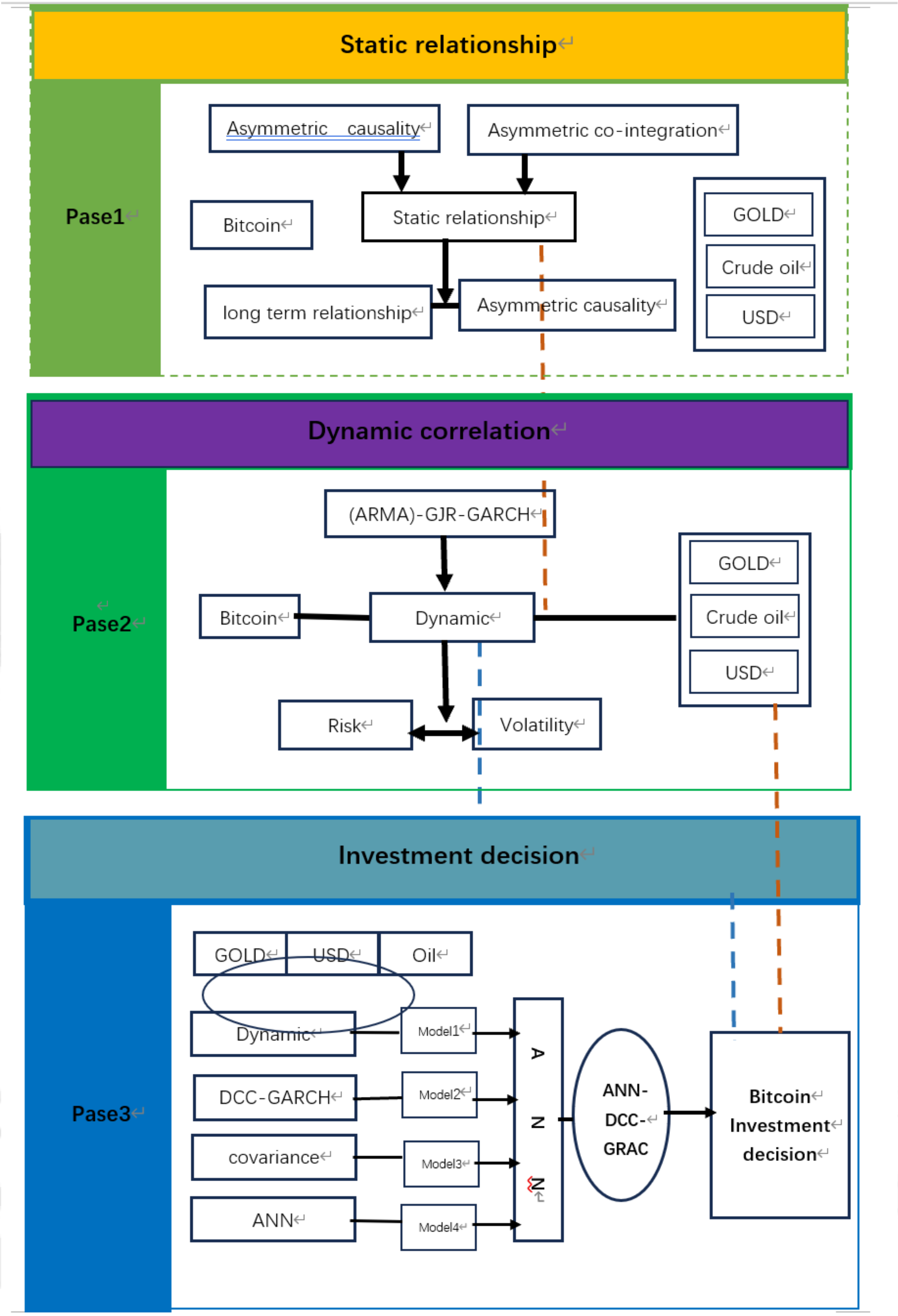

Figure 1.4 Conceptual framework

1.7 Thesis Outline

This thesis consists of six chapters, each section outlines the systematic approach used to conduct the study. The introductory chapter offers a concise summary of the context of the BTC (BTC) investigation, the framework and overall design, the problem statement, the research inquiries, goals, motivations, scope of the study, explanation of fundamental concepts, and the contributions.

The second chapter comprises a thorough review of existing literature, introducing fundamental concepts of cryptocurrencies, BTC and blockchain based on an introduction to the relevant theories, as well as relevant studies and discussions in the existing literature on the topic of this research in order to clarify the lack of sufficient evidence in the existing literature and in this study, and how recent research will address this issue.

Chapter 3 of the thesis describes the research methods. A quantitative correlation design was used in this thesis for empirical testing. The methods selected in the data processing are presented one by one, describing the process of asymmetric cointegration methods, asymmetric causality tests, autoregressive moving average (ARMA)-GJR-GRACH models, DCC-GRACH models, artificial neural networks, and ANN-DCC-GRACH methods. The study presents both current perspectives and potential trends over time.

Chapter 4 discusses the comparison of the asymmetric relationship between BTC and Gold, Crude Oil and US Dollar before and after the COVID-19 outbreak, and demonstrates the static relationship between BTC and Gold, Crude Oil and US Dollar through data selection, empirical analysis, and results presentation.

Chapter 5 of this thesis discusses the measurement of dynamic correlation between BTC, crude oil and gold, through data selection, empirical analysis, and conclusion elaboration. The dynamic correlation between BTC, crude oil and gold is argued.

Chapter 6 uses the correlation between BTC and traditional financial assets, including static correlation and dynamic correlation, and other factors introduced into the investor's investment decision, through the selection of data, empirical analysis, and the results of the exposition of the argument that the ANN-DCC-GARCH method whether there is helpful to the investor's investment decision.

Chapter 7 encapsulates this thesis. It will succinctly recap the primary discoveries, delineate their implications, and propose future avenues for research. Furthermore, this chapter will underscore the limitations of the thesis.

CHAPTER 2

LITERATURE REVIEW

As a representative of digital currencies, BTC has garnered widespread interest and research across diverse disciplines, including the field of finance, science and technology, and society due to its high price volatility, market ups and downs, and increased investment risks. Currently, the literature on BTC price prediction focuses on various research methods and techniques, like conventional fundamental analysis, technical analysis, time series analysis, and the utilization of state-of-the-art technologies like machine learning and (AI) artificial intelligence that have surfaced in recent times. This literature covers a variety of time scales and research perspectives from the near term to the extended term and from the micro to the macro. A web search reveals that from 1990 to 2022, there are more than 5,000 articles on price forecasting. In contrast, the literature on investment forecasting began to emerge in 2014, and by the end of 2022, there were less than 400 articles. The objective of this preliminary quantitative investigation is to examine the correlation between BTC and conventional financial assets, such as Gold, Oil, and the U.S. dollar. and leverage this correlation to analyze the price movement of BTC, aiding investors in making effective investment decisions, particularly with respect to the fluctuations in BTC price pre and post the COVID-19 pandemic. The purpose of this literature review is to assess the existing body of literature in order to establish a foundation for the research problem statement.

Chapter 2 systematically reviews the literature on the concepts, related topics, and literature on the core variables associated with the basic theories of cryptocurrencies, BTC, and blockchain. It also outlines the relevant theories used in the article, encompassing concepts like the effective market hypothesis, the theory of stochastic walks, the stock price mean reversion theory, the modern financial market theory, the value investment theory, and the diversification theory, these form the foundational principles of the theoretical framework. Scholarly articles subjected to peer review were sourced from the SCOPUS and Web of Science Compilation databases, relying on a amalgamation of prevailing literature. The search subjects employed to find the literature comprised BTC, BTC's relationship and impact on Gold, Oil, and the U.S. dollar, BTC's ever-changing correlation, BTC's investment predictions, and COVID-19. Extra exploration keywords included information asymmetry hypothesis and efficient capital markets hypothesis. In the end, this dissertation also delivers a bibliometric and visual examination of the BTC research domain. This literature survey discusses various theories regarding the connection between BTC and the efficiency of capital market information. In addition, studies in the existing literature related to the comparative analysis of investment forecasting problems are presented. The discussion revolves around the debate on whether machine learning models surpass traditional statistical analysis. This establishes the fundamental research framework for this thesis. The literature review not only highlights but also reinforces the research direction of the thesis. In conclusion, there is a growing imperative to broaden BTC research into capital market investments, particularly within China's emerging markets. This will encourage the prolonged, superior evolution of financial markets while fostering collective benefit for all parties involved.

2.1 Foundational Principles of cryptocurrencies

In this segment, we scrutinize the fundamental concepts of cryptocurrencies from a monetary perspective. First, it discusses the progression of digital assets and then discusses their advantages and disadvantages. Finally, BTC, the most widely known cryptocurrency, explains its underlying technology: the blockchain.

2.1.1 Cryptocurrency Evolution

Together with economic growth and technological progress, the quest for simplicity and safety of transactions has resulted in a transformation in the shape of currency (Rahardja et al., 2021). Before discussing digital currencies, a review of the development of money reveals that there are a variety of definitions and classifications of money (Brunnermeier et al., 2019). At first, currency was characterized by its role, and it was seen as a universally acknowledged object that could be utilized for purchasing goods and services and for resolving debts.

In the current era, an increasing number of payment methods such as Alipay, WeChat Pay, Libra, and M-Pesa are extensively employed (Adrian & Mancini-Griffoli, 2021; Brunnermeier et al., 2019; Eichengreen, 2022). Khan et al. (2017) Indicated by the progressive spread of cashless payment techniques, the advancement of online transactions has resulted in the swift surge of virtual currencies and the ongoing enhancement of payment instruments. Through the ongoing exploration and advancement of virtual currencies, the interpretation of virtual currencies by central banks and academics globally is also changing. From the perspective of scholars and major central banks, digital currencies in a broad sense are various types of electronic and digital alternative currencies that are subject to different degrees of regulation, including virtual currencies, cryptographic digital currencies, electronic currencies and legal central bank digital currencies (Barrdear & Kumhof, 2016; Fama, 1970a; Gregoriou & Nian, 2015).

In contrast to the way the world's leading central banks and academics have defined digital currencies. In 2021, the International Monetary Fund (IMF) issued a dedicated publication on electronic currency; The Rise of Digital Money, which proposed a new framework for defining various payment methods in terms of four attributes: type, value, backstops, and technology (Adrian & Mancini-Griffoli, 2021) based on the four main attributes of the above payment methods. Figure 2.1 notes digital currencies can be divided into five categories, namely central bank digital currency (CBDC), crypto-currency and other rights-in-kind currencies, as well as B-money (Bank money) issued by banks, Digital currency (electronic currency) provided by private entities, and I-money (investment money) offered by private investment funds. CBDC, cryptocurrency, and B-money (Bank money), Digital currency (electronic currency), and I-money (investment money) provided by private investment funds. According to Adrian & Mancini-Griffoli (2021), a central bank digital currency replaces the physical manifestation of currency and achieves the comprehensive digitization of paper money; specifically, the central bank digital currency serves as a digital rendition of the official currency.

The money flower: a taxonomy of money

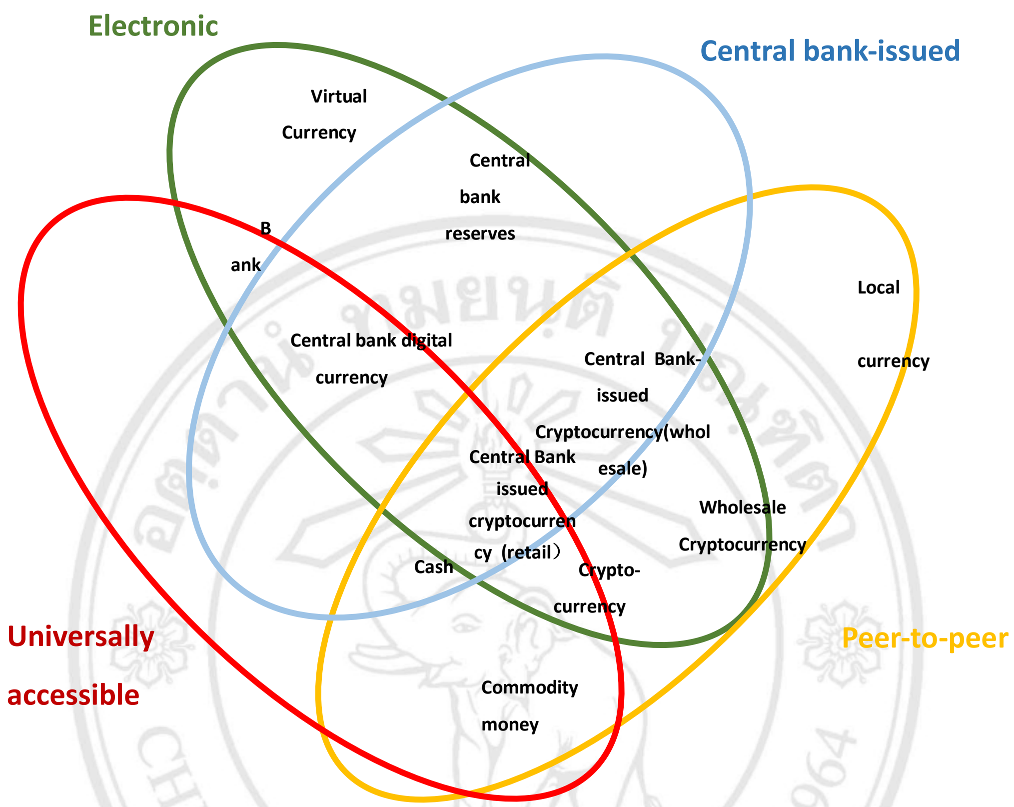

Figure 2.1 Source from: Adaptation from Bank for International Settlements (2017)

The advancement of virtual currency is intricately connected to the support of digital technology. In recent years, advancements in modern technologies such as wireless internet, vast data, machine intelligence, interconnected devices and block series have boomed, bringing about the expansion of technology-driven innovation. Blockchain technology is currently the main technical support for digital currencies and has received unprecedented attention from the public and scholars, becoming one of the most popular digital technologies, frequently known as "distributed ledger technology" (DLT). Back in the 1990s, Haber and Stornetta (1990) suggested a method for dating digital document files and creating related historical data logs, or more precisely, a protocol that could easily detect whether the records had been tampered with, which is very similar to the underlying technology of BTC and is the earliest source of concepts related to blockchain technology.

However, the real opportunity for blockchain to rapidly gain popularity came when Berentsen (2019) released a white paper on peer-to-peer payment systems following the U.S. housing market crash, officially creating the first open source, decentralized virtual cryptocurrency, BTC. Since then, a number of virtual cryptocurrencies have emerged that are similar to BTC, and blockchain is the main innovation in virtual cryptocurrencies, gaining fame as the underlying technology for cryptocurrencies such as BTC (Beck & Müller-Bloch, 2017). And considering its potential benefits in cost efficiency, speed, and security, it is now attracting the interest of many institutions and companies and is gradually expanding its application in various fields such as logistics, trade finance and financial transactions (Wörner, 2016).

According to the summary of on the research (X. Zhang & Chen, 2019) related to blockchain technology in recent years, Benisi et al. (2020) can be seen as a distributed repository for housing and relaying decentralized information. Moreover, every block represents data created through distributed accord mechanisms, cryptography and encryption algorithms, etc. (Bodkhe et al., 2020). These data blocks continue to grow and connect to form an ordered. These data blocks are continuously growing and connected to form an orderly data chain, which records the transaction logs of all users in the network and has many features such as openness, anonymity, sharing, autonomy, tamper-proof, and traceability. Consensus mechanisms are at the heart of blockchain technology, and Ferdous et al. (2021) asserts that the triumph of BTC depends on three varieties of agreement: a consensus on rules; a consensus on a unique ledger, and a consensus that BTC has value.

According to the different participation methods, the contemporary block series system can be categorized into open block series, closed block series, and union block series (Zheng et al., 2018). In an open block chain, all data is visible to the general public, and anyone can engage in the block chain consensus process while maintaining anonymity (Ferdous et al., 2021). A closed block chain is entirely overseen by a designated corporation, and solely the nodes from that corporation are permitted to exchange information, so a private blockchain is also considered as a centralized network structure; while a consortium chain formed by multiple organizations is partially decentralized and transactions in the network are verified by a group of selected nodes. Most of the well-known virtual cryptocurrencies use the public chain approach, and BTC and Ether are examples of applications based on public chains and cores.

The Evolution of Digital Currency

The progression of currency is examined from the standpoint of the advance of financial technology. Essentially, Financial Technology (fintech) concerns the innovation and implementation of scientific and technological advancements within the fiscal sphere, entailing the profound amalgamation of cutting-edge technologies and economic requirements (Brandl & Hornuf, 2020; Gomber et al., 2018). The underlying significance of Financial Technology (fintech) encompasses the financial transformation prompted by the technological upheaval, yielding novel commercial frameworks, applications, procedures, or commodities that profoundly influence the provision of specific financial services, and even the financial market on the whole.

The evolutionary chronicle of currency begins with Physical (commodity) currency, which transpired initially in the progression of commodity trade among human societies. (Britchenko et al., 2020). Physical (commodity) money is the first form of money produced in the development of human society in the process of commodity exchange (Polanyi, 2018). Tangible coins are an important form of money development process. Tangible coins are mainly divided into two categories: metal coins and paper money (Grünewald et al., 2021). Metal coins are divided into precious metal money (full value) and ordinary metal money (low value) (Monroe, 2020). Initially, the actual metal content of coins was equal to the nominal metal content (Scrivano et al., 2022), and the actual and nominal values of metal coins were gradually separated, and the popularization of ordinary coins marked the entry into the primary stage of credit money form (L. Ma & Li, 2019). After the first millennium A.D., the earth gradually shifted to the usage of paper currency (Taskinsoy, 2019b), and the emergence of central banks and other authorized financial institutions played a role in the gradual standardization of official currency, and the widespread use of official currency signaled the advanced phase of credit money (Bouman, 2019; Do Vale, 2021; Sharov, 2020; Xia et al., 2023). Invisible digital currency embodies the future path of currency evolution. Following the industrial revolution, with the revolution and advancement of information technology (Fitzsimmons, 1994). Electric technology and network communication have emerged as a critical instrument for societal interaction (Sima et al., 2020). Digital payment methods have gained traction in economic activities, replacing traditional paper currency with electronic forms. The swift growth of virtual currency post-2000 has attracted the interest of governments globally, with central banks of various countries placing significant value on new digital currency types founded on blockchain technology in 2013. Progressing from the progression of digital currency to virtual currency, categorically, all fall within the range of intangible digital currency, serving as a response to the digitization trend of currency in the Internet era (Bolt & Van Oordt, 2020).

In short, the fundamental progression of the monetary norm encompasses three primary phases: the metal norm, the Bretton Woods amendment, and the credit norm (Kugler & Straumann, 2020). The metal benchmark, the Bretton Woods adjustment, and the credit guideline. If the physical money before the precious metal money is taken into account, the metal standard actually includes and represents the commodity standard, and the Gold standard is the most famous representative of the metal standard (Vasantkumar, 2019). For example, Britain officially implemented the Gold standard in 1816, Germany embraced the Gold benchmark in 1873, and the U.S adopted the Gold standard in 1900 (Taskinsoy, 2019a). However, upon the onset of the First World War in 1914, the Gold standard was suspended (Taskinsoy, 2019a). In the 1920s, Austria, Germany, the Soviet Union, Britain and France successively restored the Gold standard. Subsequently (Simmons, 2020), the Gold standard system did not last long, for example, in 1931, Austria, Germany and Britain gave up the Gold standard system, in 1993, the United States implemented the Gold embargo (which lasted until 1974), and in 1936, France also gave up the Gold standard system (Pigeaud & Sylla, 2021). In terms of practical implementation, the Gold standard approach has encountered diverse stages including the Gold coin standard variation, Gold standard variation, and Gold exchange standard variation, among others (Accominotti, 2020). In simplified terms, the metal standard system includes the Gold and silver compound standard, the Gold standard and the silver standard (Eichengreen, 2019) . However, it should be noted that the Gold standard is not the dominant metal standard. On the one hand, most countries were on the compound standard (Gold-silver or silver-copper) before the Gold standard became common in the West in 1870 (Karaman et al., 2020). Conversely, temporally speaking, the Gold standard did not prevail as the prominent metal norm. In terms of time, the Gold standard system lasted less than 50 years (1873-1914, 1925-1931) , and silver currency was the longest and most widely used in history, but basically it was a Gold-silver or silver-copper compound standard (Eichengreen, 2019, 2019; Taskinsoy, 2019c). So "in the period of the metal standard (before 1935) the compound standard is the prototype, the Gold standard, silver standard, GES (Note: Gold exchange standard) are all exceptions or variants of the compound standard " (Wilson, 2017).

Following the Second World War, the Bretton Woods accord symbolized an interim phase in the shift from the commodity-oriented monetary standard to the credit-oriented monetary standard. (Redish, 1993). Frankel (1999) was typically characterized by a double peg - other countries' currencies were pegged to the US dollar. And the US dollar was fixed to Gold, and the maintenance of Gold parity was in essence an international Gold-exchange standard (Accominotti, 2020). Because theoretically speaking, following the abandonment of the Gold standard in France in 1936, there was no longer any kind of currency that was convertible as far as the sovereign state was concerned (Bernanke & James, 1990). Paper money replaced metal, and the value of money was no longer determined by the material it contained, but by the purchasing power it conferred (Fisher, 2006). The Bretton Woods system lasted for about 30 years, the restoration of the external convertibility of the British pound failed in 1947, the pound was devalued twice, in 1949 and 1967 (Helleiner, 1996). The IMF's first constitutional amendment created the Special Drawing Rights in 1968, the US dollar ceased to be convertible and was devalued in 1971 (Kugler & Straumann, 2020). The currency was fully floated in 1973 - a de facto break-up of the Bretton Woods system (Vernengo, 2021). The second modification to the IMF's Articles of Association gave up the fixed parity and Gold was no longer a reference. The era of the credit standard came fully and completely, and the US dollar remained the most important international currency (Bordo, 1993). Regarding the progression of the monetary norm, the composite norm within the metal standard holds a predominant status, while the dollar under the credit standard after the Bretton Woods system is actually a compound standard despite being the dominant international currency (Eichengreen, 2011). This is evident in the importance of the "composite average" of the U.S. dollar index and the Special Drawing Rights (SDRs) (Pham, 2019).

Throughout the history of currency evolution, the development of currency format results from the combined effect of societal needs and technological provision. (Choi et al., 2020). From the perspective of demand, the transformation of currency format caters to the transactional requirements of individuals. With the progress of society and the economy, individuals will articulate fresh demands regarding currency utilization to enhance the effectiveness of market transactions (L. Tao, 2021). From the supply side, advancements in science and technology facilitate the potential transformation of currency formats (Dujak & Sajter, 2019), and the form of currency chosen is determined by the technological level at that time (Ilham et al., 2022), and the selection and use of currency materials are closely related to the industrial technology of a certain era (Davis & Holt, 2021). Social demand is the basic driving force for the evolution of digital currency (Carayannis & Morawska-Jancelewicz, 2022). From the viewpoint of demand level, digital currencies have evolved to meet people's different demand levels (Tong & Jiayou, 2021), primarily involving: initially, to satisfy the populace's need for rapid and efficient transactions, i.e. digital currencies replacing banknotes (Siek & Sutanto, 2019). Second, to meet people's demand for the stability of the value of currencies, i.e. to solve the problem of indiscriminate issuance of digital currencies by using the blockchain technology to mine (Wronka, 2022). Third, to accommodate the requirement for consistent usage of digital currencies globally, such as the global uniformity of currencies, and more. Saberi et al. (2019) indicated that the provision of technology was a substantial foundation for the progression of digital currency. Baek and Elbeck (2015b) Baek and Elbeck (2015b) expressed that the technological stage of society impacts the selection of currency format, and technological breakthroughs like mobile communications and big data have supplied robust technological backing for the progression of digital currencies. From the peer-to-peer network infrastructure to the utilization of blockchain technology (Attaran er.al, 2019; Gururaj et.al, 2020; Priyadarshini, 2019; Saghiri, 2020), the security and confidence issues in the advancement of digital currencies have been more effectively addressed, giving them the attributes of distributed, decentralized, tamper-resistant, and cryptographic security.

The practical necessities of the progression of digital currency investigation. The investigation and exploration of digital currency has conformed to the actuality of the fusion of contemporary societal demands and the advancement of information technology (Dwivedi et al., 2022). First, it adapts to the needs of people's understanding and application of digital currency (Mosteanu & Faccia, 2020). By means of comprehending the theory and proliferation of the digital currency framework, it will assist individuals in effectively adjusting to the economic environment during the digital currency era and partake in the encompassing impact of financial creativity (Hacioglu, 2020).

Additionally, it is essential to lead financial establishments to judiciously utilize financial technology and corporate creativity to engage in organized rivalry (Du & Wei, 2020). As there is no distinct criterion for the release of virtual currencies, prominent corporations are racing to introduce their individual virtual currencies, resulting in numerous virtual currencies being issued globally. It is imperative to set up uniform norms and systems for digital currencies, enhance insights into the function of financial institutions within the digital currency system, and sensibly exploit fintech methods and assets to conduct regulated competition within the financial sector (Norwood & Peel, 2021). Third, it is necessary to respond to the international competition in digital currency research and development practices of central banks and the challenges of financial security (Dikau & Volz, 2021). In response to the exploration and practice of digital currency innovation, central banks of various countries are actively paying attention to it, and in 2015, the Bank of England spearheaded the declaration of exploring and creating digital currency underpinned by blockchain technology (Auer et al., 2020). Acknowledging the credit theory of virtual currencies and delving into the creation of risk control mechanisms, and dovetailing with the central bank's practice of digital currency innovation and regulation will help accelerate the implementation of legal tender digital currency and take the lead in building the foundation for financial digitization in the international cyberspace (L. Cao, 2023).

Cryptocurrency Exchanges

A cryptocurrency exchange is an online website or application where investors can buy, sell, or convert their cryptocurrencies to other currencies (Fang et al., 2022; Murray et al., 2023; Saksonova & Kuzmina-Merlino, 2019). Cryptocurrency exchanges generally support around 20 or more of the most widely used cryptocurrencies in relation to market value. (La Morgia et al., 2020; Pessa et al., 2023). One of the essential features that digital currency exchange should have is the high security of transactions (Khan et al., 2019). In addition to security, user friendliness and transaction fees are other factors that affect the choice of an online exchange. In the following, some of the best digital currency exchanges are introduced.

Coinbase

At present, CoinBase holds the top position and most popular trading platform for cryptocurrencies in the United State especially for BTC (Ibrahim et al., 2021). Also this platform supports trading of some other currencies BTC Cash, Litecoin and Ethereum. The platform can also provide digital currency wallets and digital currency exchange services at https://www.coinbase.com/.

Bitstamp

Bitstamp is a BTC and digital asset exchange founded in 2011 and headquartered in Ljubljana (Soska et al., 2021). Bitstamp is among the earliest and highly regarded BTC (BTC) exchanges in Europe (Catania & Sandholdt, 2019), and it is a strictly regulated exchange that is supervised by several regulatory bodies, including the Central Bank of Lebanon, the Luxembourg Financial Supervisory Authority, the UK Financial Conduct Authority and others. Bitstamp currently offers its services to users in over 100 countries and territories.

Bitfinex

Bitfinex is a digital currency trading platform, possessed and managed by BitFinex. It is based in Hong Kong and officially listed in the British Virgin Islands. In 2015, shareholders suffered roughly $400,000 in losses due to a security breach at the exchange. In 2016, approximately $730,000 was stolen from customer accounts on its exchange. In October 2018, Bitfinex's relationship with banking ran into another crisis. Its leadership group stated that "Bitfinex was not bankrupt on October 7." Studies reveal that Bitfinex's manipulation of BTC prices contributed to approximately half of BTC's price surge in late 2017. That same year, Bitfinex was announced as an EOS Super Node candidate team. At the time of writing this study, there are nearly 300 cryptocurrency exchanges. The graph displayed in Figure 2.2 illustrates the market share of the top 5 cryptocurrency exchanges. Coinbase exchange shares 27.78% of the market share, which is the highest share of all exchanges. This is followed by the Bit-x exchange with 19.1% of the market share. Kraken also has a large market share at 17.85%.

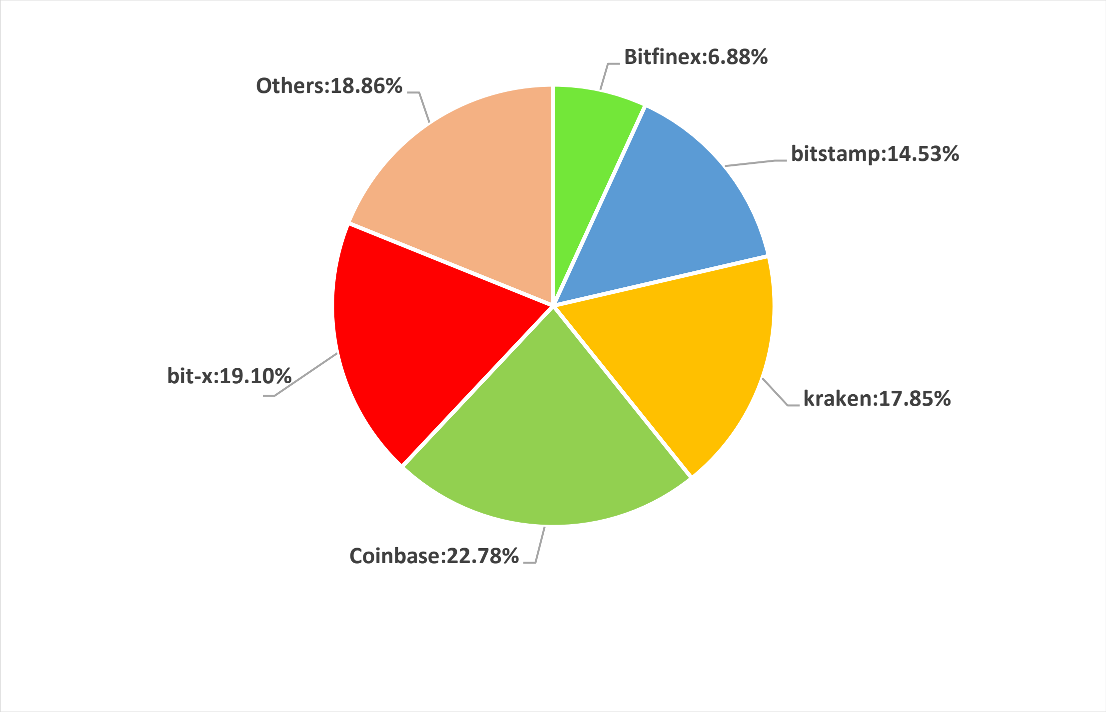

Figure 2.2 Market shares of Top 5 cryptocurrency exchanges

Data: From 1 December 2023 to 31 December 2023

Cryptocurrencies Classification by Well-known Policymakers

Emerge of cryptocurrencies might be leading to a technological revolution in the future. Thus, it is deemed necessary to make policies on cryptocurrencies. Therefore, policymakers around the world have come to classify cryptocurrencies to be known in the financial systems. Table 2.1 presents the cryptocurrencies classification by policymakers.

Table 2.1 Cryptocurrencies classification by policymakers

POLICYMAKERS	CLASSIFICATION OF THE CRYPTOCURRENCIES
The European Central Bank (ECB)	A portion of digital currencies, or more precisely, "unregulated electronic currency, typically created and overseen by its creators, and adopted and embraced by the participants of a particular virtual society."(Kahn et al., 2022)
International Monetary Fund (IMF)	A segment of virtual currencies or electronic representations of worth released by private creators and valued in their monetary unit. (Nawang & Azmi, 2021)
Bank for International Settlements (BIS)	Digital currencies similar to commodities like Gold but wi th no intrinsic value and without intermediaries for P2P ex changes are not running by any specific institution(Pandia n et al., 2023).
The European Banking Authority (EBA)	A portion of digital currencies pertains to "representations of worth that are not issued by a central bank or governmental entity and are not inherently linked to a fiat currency but are utilized by individuals or entities as a medium of exchange and can be electronically transferred, stored, or traded."(Alsalmi et al., 2023).
The European Securities and Markets Authority (ESMA)	Cryptocurrencies are described as "digital depictions of worth that are not issued or endorsed by a central bank or government authority and do not hold the legal standing of traditional currency or money."(Nath, 2020).
The World Bank	As a subset of digital currencies or "digitally represented value that is valued in their unit of measurement, distinct from digital money, which is exclusively a digital method of payment, symbolizing and valued in fiat money." (Nawang & Azmi, 2021)

Table 2.1 Cryptocurrencies classification by policymakers (Cont.)

POLICYMAKERS	CLASSIFICATION OF THE CRYPTOCURRENCIES
The Financial Action Task Force (FATF)	As elements of online currencies, they are characterized as "digital depictions of worth that can be digitally traded and function as a medium of exchange, a unit of measurement, or a repository of worth, but are not acknowledged as legal tender in any jurisdiction."(Lone et al., 2020).

Modern Monetary Theory on Cryptocurrencies as Money

Modern Monetary Theory (MMT) is a macroeconomic theory that describes most countries' fiat currency system since 1971 when the US dollar is not backed by Gold anymore (Siddique, 2022). Contemporary Monetary Theory (CMT) underscores attaining stability in prices and full employment through the utilization of currency as a mechanism. Keynes's perception of currency, impacted by (Knapp,1924), anticipated the development of MMT. Knapp coined the term "Chartalism" and claimed that the state could create paper money and make it exchangeable by knowing it as legal tender. Proponents of MMT, Armstrong (2015) argue that MMT acknowledges that the money supply is under public control. The main idea of MMT is that governments can print money as much as they need to spend because they do not go bankrupt. Traditional thinking says that spending much leads to substantial debt and high inflation. Nevertheless, under modern monetary theory, high debt does not cause insolvency (Wray & Nersisyan, 2021). A small deficit or surplus can be severely harmful and cause stagnation because this deficit shows people's savings. The debate here concerns whether cryptocurrencies are able to serve as a substitute for traditional currency within the MMT framework.. Tymoigne (2013) holds views opposing the use of BTC as an MMT tool. He illustrated some arguments as follows:

1) According to MMT, the budget deficit is better than the budget surplus (Bohn & Inman, 1996). To combat inflation caused by the budget deficit, the government determines taxes and issues bonds, implying that money scarcity is a political decision.

The Federal Reserve Bank issues dollars and promises to accept them in payments to take it back in taxes or bonds (Cochrane, 2022). So, the Demand for the dollar is met, and people collect the national debt. In contrast, cryptocurrencies do not have any government backing, which requires people to make payments with them. In that context, it doesn't have a ultimate demand and thus has no inherent worth, and its just value would decrease to zero.

2) Under the MMT, supply changes with the quantity demanded, whereas cryptocurrency is in fixed supply (Shipman, 2019). For instance, the BTC supply is determined to be 21 million.

2.1.2 Cryptocurrency Advantages and Disadvantages

Cryptocurrency, as an emerging phenomenon, has its advantages and disadvantages (Astuti et al., 2022). Following this section will talk about the most important advantages and disadvantages.

Cryptocurrency Advantages

Regarding the advantages of digital currencies, scholars' research and elaboration mainly focus on the following aspects:

Convenience

In contrast to conventional currency, the adoption of electronic currency will significantly alleviate the inconvenience of transporting tangible cash (Liao & Caramichael, 2022), and this exchange of worth is immediate and person-to-person (Brunnermeier et al., 2019). The introduction of electronic currency and transactions has empowered individuals to better assimilate into the digital era, as demonstrated by the widespread use of WeChat and Alipay transactions in China.

Improving the efficiency of cross-border payments

When it comes to international transactions, virtual currencies are more cost-effective, swifter, and considerably more effective in contrast to payment means like physical currency and bank account deposits, facilitating smoother cross-border transactions and consequently advancing the scope of digital currencies (Hetal & Ashok, 2020).

Low-Cost transactions

The cost of transactions and transfers using digital currencies is significantly lower, without the hassle of currency note production and currency creation, and transactions are rapid and immediate, rendering them more appealing than standard currency payments (Moin et al., 2020).

Traceability and trust worthiness

First, due to the nature of technologies such as blockchain, digital currencies have the advantage of being both traceable and difficult to tamper with data. Secondly, the bankruptcy of Lehman Brothers after the subprime crisis in 2008 led to a swift downturn in the U.S. and the global economy. Van der Cruijsen et al. (2021) assert that one of the primary factors for this downturn was the significant decrease in confidence in the monetary industry and the economic structure overall. According to polls, individuals generally rely on and prefer major technology corporations over the financial sector, such as community banks (Salem et al., 2019), due to the fact that major technology firms are usually robust rivals in creating perceptions of increased value and improved interactions for users (Tekic & Koroteev, 2019). In turn, confidence boosts the readiness of consumers to experiment with financial services provided by technology corporations. Thus, certain digital currencies are frequently launched with the backing of technology behemoths.

Network effects

The network effect of the Internet, which is now relatively mature, allows for the rapid global diffusion of novelties. As a consequence, it can have beneficial ripple effects on society as a whole driving strength (Auboin et al., 2021). For example, the use of E-money has typical network externalities (Davoodalhosseini & Rivadeneyra, 2020) . One option is to incorporate it into prominent social networking applications to achieve digital transactions, which has a wide user base and a large user growth potential (Torous et al., 2021). Conversely, as the number of users gradually rises, it will further increase the value to all existing and potential participants in the E-money system (Nishibe, 2020). As the number of users gradually increases, it will further enhance the value to all existing and potential participants in E-money system (Abdillah et al., 2019).

Cryptocurrency Disadvantages

The vast majority of scholars believe that private digital currency payments have a negative impact on the economy in many ways (Adrian & Mancini-Griffoli, 2021). This includes significant financial, security and environmental risks, all of which negatively impact the development of cryptocurrencies (Tao et al., 2022; Tkachenko et al., 2019; Wang et al., 2022). It also creates new challenges for countries to regulate cryptocurrencies. The utilization of digital currencies for illicit activities and unlawful transactions poses a significant hazard for this form of currency (Chawki, 2022). Although blockchain technology itself ensures the security and reliability of transactions to a large extent, it is difficult to adequately protect user information because BTC transactions are public (Perkins, 2020). In this context, the safeguarding of privacy within the cryptocurrency market and BTC is indeed weak, and malicious assailants can readily acquire valuable data, scrutinize cryptocurrency market transactions, and engage in unlawful activities (H. Zhang & Zou, 2020). The innate unrestricted and worldwide characteristic of cryptocurrency transactions utilizing blockchain technology has contributed to the cryptocurrency market becoming one of the most extensive uncontrolled markets globally (Morton, 2020). Because of its overwhelming dominance in the cryptocurrency market, BTC is inevitably the first to be exploited by criminals, bringing it a bad reputation (Chohan, 2022a). Furthermore, BTC is anonymous and many illegal criminal activities take advantage of its anonymity and loopholes in market regulation. Foley et al. (2019) highlights indicate that approximately $76 billion in illicit activities are associated with BTC annually, constituting 46% of BTC transactions. Price manipulation in cryptocurrencies has also been the focus of regulatory attention (Corbet, 2020; Corbet et al., 2019; Eigelshoven et al. , 2021; Silva & Mira da Silva, 2022). P&D (commonly known as "pump and dump") is a prevalent type of securities deception, where prices are falsely adjusted for financial gain through the dissemination of inaccurate and deceptive information (Krishnan et al., 2022). In recent times, digital currencies have gained traction among numerous investors as a fresh form of speculation, and P&D deceptive price adjustment is widespread within the digital currency market (Kamps & Kleinberg, 2018). Due to regulatory gaps in digital currencies, which lead to the frequent incidence of questionable transactions, making them exceedingly susceptible to price manipulation. The BTC Exchange at Mt. Gox, the most extensive digital currency exchange globally, experienced substantial BTC price fluctuation during a specific period (2013-2014), the conversion rate of the American currency against BTC increased by an average of 4 percent when suspicious transactions were present, while exchange rate declined relatively when there was no suspicious activity.

Concerns related to the environment, such as preserving energy and reducing emissions, have also arisen alongside the widespread use of cryptocurrencies (Howson & de Vries, 2022). Digital currencies were not initially created considering the possible environmental consequences, and as they gain more traction miners must work harder to "mine" them to obtain them, a computational process that utilizes substantial quantities of power and is progressively reliant on highly specialized hardware apparatus (Lally et al., 2022). Li et al. (2021) investigates the power usage of digital currency extraction by employing the instance of the Monroe coin, indicating that Monroe extraction consumes 645.62 gigawatt-hours of worldwide electricity annually. This represents 0.55% of worldwide electricity production, approximately equal to the yearly energy usage of a minor nation like Malaysia or Sweden (Carter, 2021). Undoubtedly, the substantial energy consumption of cryptocurrency mining has an undeniable adverse impact on the environment (Wang et al., 2022). Delina (2023) suggests regulatory approaches and policy options for decarbonizing digital cryptocurrencies with respect to environmental and energy consumption issues. As the first option, it is necessary to adopt regulatory measures to reduce the energy consumption of mining in countries that conduct a lot of mining activities (Fadeyi et al., 2019), and technical standards can also be set to restrict indiscriminate mining activities. Secondly governments can impose tariffs or excise taxes on imported mining equipment based on energy consumption, and high value-added taxes and profit surcharges on domestically produced equipment. Furthermore, they can require the registration of all types of mining equipment and impose tiered fees based on environmental indicators such as emissions. In addition, increasing the price of energy can be an effective measure to reduce energy consumption.

Destabilization of the financial and monetary payment system. It is well known that traditional cryptocurrencies are highly risky and their negative impact on the operation of financial markets and monetary systems is self-evident. Therefore, along with the popularity of cryptocurrencies, stablecoins are rapidly emerging as a new type of relatively stable cryptocurrency instrument (Board, 2020; Kolodziejczyk & Jarno, 2020).

However, the value of stablecoins is not overwhelmingly "stable". In theory, the distinguishing features of stablecoins are low volatility, security, and stability, but in practice the results have not been as satisfactory (Sidorenko et al., 2019). The market value and stability of stablecoins are also affected by the corresponding linked assets or mechanisms due to their linkage to different assets and the existence of different collateral mechanisms (Bullmann et al., 2019). Simultaneously, the misbehavior of stablecoin issuers can also cause fluctuations in the price of stablecoins when the regulatory system is still incomplete. For example, one of the most globally watched stablecoins, the Scales, has many potentially significant risks despite multiple versions of design changes (Schmeling & Wagner, 2019). First, the reserve assets of the Scales are mostly composed of highly traded and stable currencies, and therefore, the value of the Scales varies with the market value of the reserve assets backing them a phenomenon that is very similar to that of securities investments, with holders of the Scales suffering corresponding losses in the event of adverse changes in market conditions (Arslanalp et al., 2022). At the same time, the widespread use of the scales means that a large amount of foreign exchange reserves will be concentrated in the scales, which will increase the systemic risk and the difficulty of foreign exchange control in each country. Second, the widespread adoption of the Scales could potentially disrupt the central bank's financial strategy transmission mechanism and its control over the payment system on a large scale, contradicting the stability of the Scales. An important reason for the stability of the Libra coin is the stability of the legal reserve assets backed by the central bank, but the launch of the Libra coin may limit the central bank's ability to perform the corresponding function, thus weakening the safety and stability of the Libra coin. Third, the widespread adoption of the Scales will inevitably lead to a strong demand for its derivatives and credit products in the system to hedge exchange rate risks, increase financial leverage, and further lead to more regulatory issues.

2.1.3 BTC and Blockchain

In October 2008, someone called Satoshi Nakamoto put forward a peer-to-peer payment system design in his article. Some considered his work a new scam, while others believe his criticism against the world banking system and the 2008 crisis strengthens his motivation. In January 2009, he created the first block of BTC, or so called "Genesis," or "block 0", which is the prototype of all other blocks in the BTC blockchain and the basis of the BTC trading system. The reward for mining the Genesis was 50 BTCs. A few days later, he provided the first open-source version of BTC software, and the next day "block 1" got mined, and after that, the initial BTC transaction was conducted between users. Purchasing two pizzas from an American pizzeria for 10,000 BTCs is the first BTC transaction in the real world that indicates he low value at the beginning. Bit Gold, had similar concepts to BTC, such as independence of any central authority, digital timestamps, and secure property titles. Like B-money, Bit Gold also never launched. There are many suspicions that the mysterious Satoshi Nakamoto is either of them. In the following, some factors show the popularity of BTC among people.

1) BTC daily transactions

Increasing the number of businesses that accept cryptocurrencies, Ghani et al.(2022) shows the growth of daily BTC transactions from 2012 to 2020. The number increases from 50 thousand daily transactions to 350000, seven times as big as before. Another phenomenon that Figure 2.3 shows people seek to have encrypted money is the number of crypto ATMs installation growth worldwide.

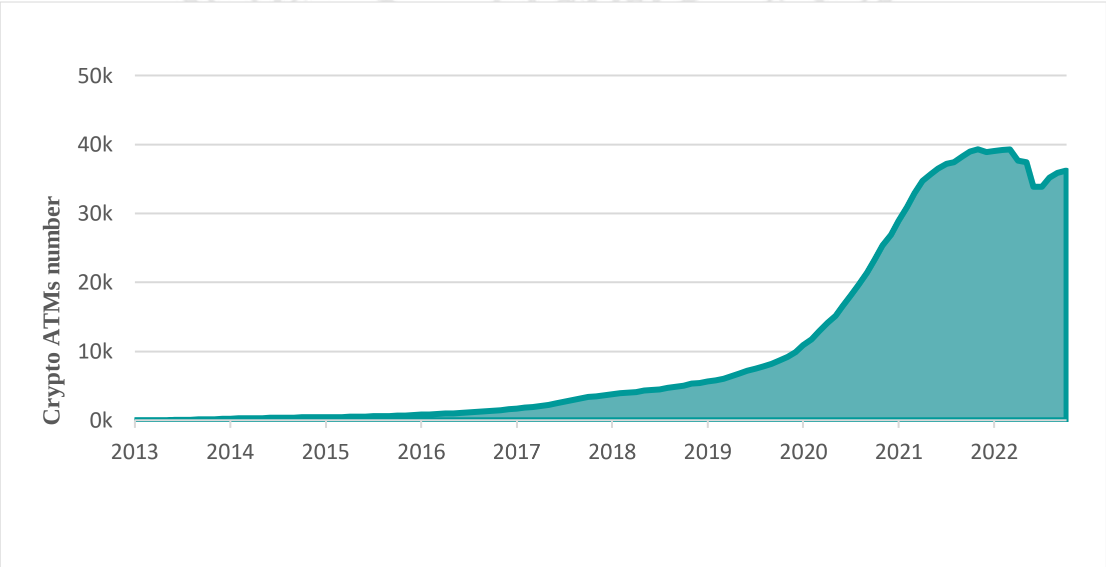

Figure 2.3 BTC ATM installations growth

Source: coinatmradar.com

How Does BTC Work

BTC uses cryptographic mechanisms to expose encrypted BTC addresses to the public and control all rights through a hidden private key (X. Zhang & Chen, 2019). The BTC address does not contain any user information, and a user can even generate unlimited BTC addresses (Manimuthu et al., 2019). BTC is therefore anonymous. A node in the network can self-identify its ownership of BTCs through its private key (Cubukcuoglu, 2022) and thus perform transactions while additional nodes authenticate the legitimacy of the transaction using the node's public key and signature (Huynh et al., 2019). Each transaction is generated is then propagated to the network and verified, and some special nodes start competing for the right to book recent transactions (Xu et al., 2019). These special nodes solve a random value that satisfies the requirements of the system by brute force computation to qualify for bookkeeping and get paid (Wu et al., 2019). The process is termed mining, and these specific nodes are called miners (Aponte-Novoa et al., 2021). Miners take the most recent transactions in the network, pack them into a block according to a specific data format, complete the bookkeeping, and link the most recent block to the subsequent block preceding the new block by allusion to create a blockchain (Xu et al., 2020). The nodes in the BTC system will automatically modify the mining complexity based on the mining power invested in the entire network, ensuring that the system is reliant on the quantity of blocks (Zhang et al., 2020). The points in the BTC system adaptively regulate the mining complexity based on the mining power invested in the network, ensuring that the system generates a new block at a rate of ten minutes. The BTC system gives a certain amount of BTC to miners who mine a new block (Iwamura et al., 2019), this is the exclusive method for generating new BTCs in the network, and it serves as the incentive mechanism. The incentive structure also encourages miners to dedicate significant computing power, establishing a formidable barrier for malicious nodes seeking to rival the network's computational capacity in constructing fraudulent blocks. (Yun et al., 2019). The block chain is actually a queue with references, and an attempt to tamper with the contents of a block requires tampering with all the blocks connected behind it. The older the block the harder it is to tamper with. It is generally considered safe to go through six blocks in BTC (Wan et al., 2019).

Therefore, Figure 2.4 shown that BTC transaction process it is difficult to counterfeit BTCs or tamper with the history of transactions in the BTC system, independent and secure cryptocurrency **system (Porras-Gonzalez et al., 2019).**

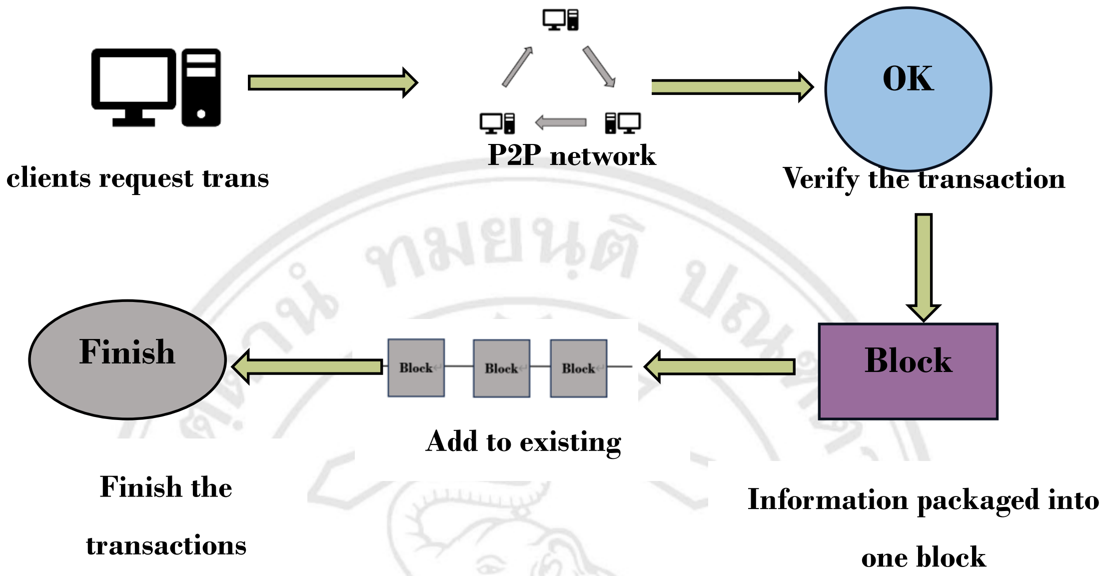

Figure 2.4 BTC transaction process

BTC Fork

BTC is a digital cryptocurrency whose value depends on market demand and supply (Iwamura et al., 2019). As the BTC market continues to expand, different factions have emerged in the community, hence the emergence of BTC forks.

A BTC fork is a new cryptocurrency formed by splitting BTC based on an improved version of the original BTC code (Chohan, 2022a). BTC forks can be categorized into two kinds: Hard Fork and Soft Fork (Zamyatin et al., 2019).

A hard fork occurs when nodes in the BTC blockchain network are updated to a new edition (Yiu, 2021). Figure 2.5 A Hard Fork shown separating the transactions and nodes of the new version in a non-backward compatible manner to form a new blockchain, resulting in a new cryptocurrency. During a hard fork, the original BTC and the new coin have different nodes and networks and are therefore not interoperable (Khan et al., 2020).

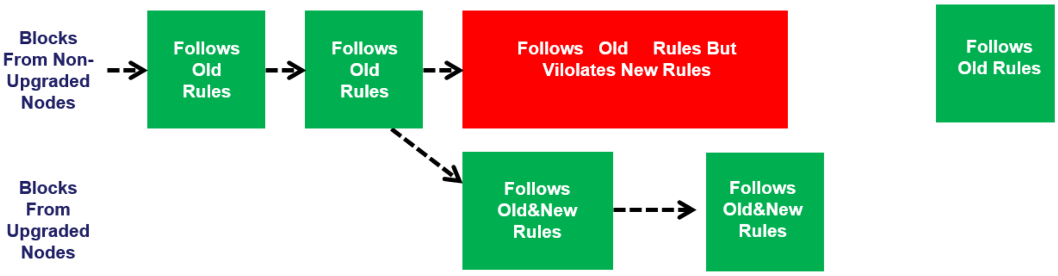

Figure 2.5 A Hard Fork: Unupdated Nodes Decline The New Regulations

Figure 2.6 shown a soft fork, It is an upgrade of the BTC protocol version, usually implemented by modifying the rules of the BTC protocol so that the new protocol can handle transactions that could not be handled in the original protocol (Zindros, 2021). In this case, the new protocol will be superior and better able to handle transactions in the original protocol (Dang et al., 2019), so most of the community will choose to accept a soft fork.

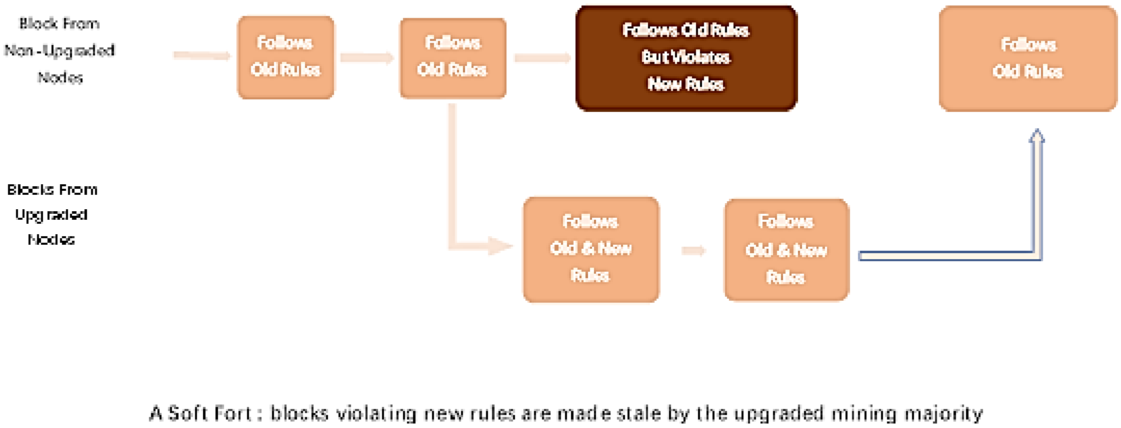

Figure 2.6 A Soft Fork: blocks infringing the new regulations are rendered obsolete

The most famous of the BTC forks is BTC Cash (BCH), which was formed in 2017 from a hard fork of BTC (Cash, 2019). The main difference between BTC Cash and BTC is the block size, with BTC Cash rising to a limit of 8 MB per block (Kwon et al., 2019), which is better able to carry more transactions than the original BTC's 1 MB (Mariem et al., 2020).

There are also many other forks such as BTC Diamond (BCD) and BTC Gold (BTG). Each fork has different characteristics and has different applications in different scenarios (Bouraga, 2022).

BTC forks can contribute to the advancement of BTC (Islam et al., 2019). Each fork has its own characteristics, advantages and disadvantages, which makes it widely applicable in different scenarios (Wang et al., 2020). However, at the same time, the increase in BTC forks can also lead to many probles. For example, forked BTC assets are not easily convertible, and can increase the cost of BTC transactions to a certain extent (Chason, 2019).

In short, BTC trading is becoming an increasingly integral part of our lives, and BTC is thriving (Chohan, 2022b). The rise of BTC forks is an unavoidable pattern in the growth of the BTC ecosystem, and more forks will emerge in the future, which will be a huge change for the BTC market.

Comparison Between the BTC, Dollar, and Gold

Blockchain

Blockchain technology was originally introduced by Scott Stornetta in 1991 as a digital framework known as "blockchain" (Modani et al., 2021). In recent years, blockchain technology has garnered significant interest from scholars in diverse domains. The blockchain comprises numerous network points with peer-to-peer connections, linked in a distributed arrangement without central points and without mutual reliance between points. The network points cooperate to uphold a blockchain framework with corresponding incentives (Xu et al., 2019). Being the fundamental underlying technology for digital cryptocurrencies like BTC, blockchain can efficiently address the Byzantine fault tolerance problem and the issue of double spending, which digital currencies have encountered for an extended period.

Historically, social reliance has relied on credit "backing" systems and trusted mediators, and relied on trusted third-party entities or entities, such as financial institutions, for reliability. However, creating a trustworthy association between two entities without a trusted third-party entity is challenging. Blockchain technology possesses the capability to resolve the trust establishment dilemma among nodes in a decentralized system through consensus mechanisms and transaction validation by distributed nodes. This ensures the decentralization of the trust system between nodes (Wang et al., 2020). Even though blockchain has existed for over ten years, initial research concentrated on the safety and resilience of the BTC system, while there was relatively less investigation into blockchain technology. In recent years, with the notable traction and progress of virtual digital currencies like BTC, the utilization and progress of blockchain technology in various sectors have also exhibited a remarkable surge (Wang et al., 2020) . Distributed ledger technology extends beyond its chained data structure and is an innovative technology for verifying transactions and sharing data by integrating methods such as ring signature, zero-knowledge proof, electronic signature, and homomorphic encryption. This ensures that the chain nodes are not reliant on a sole central entity.

Key Technologies for Blockchain

Electronic signature was initially proposed by Whitfield Diffie and Martin Hellman in 1976 (Diffie & Hellman, 1976), and is an electronic signature of an electronic document by the signer, which makes it impossible for the signer to deny or repudiate the signature signed, and achieves the same function as a handwritten signature. Uneven cryptography is the essential technology of the digital signature system, wherein every user possesses a pair of keys, namely the public key and private key, where the public key is utilized for the validation of the digital signature , and the private key is utilized for the generation of the digital signature (Imam et al., 2021). The digital signature scheme should have at least the following three conditions: 1) the signer cannot deny the signature of the message afterwards, 2) the receiver can verify the authenticity of the signature and cannot forge it, 3) when the receiver and the signer dispute the legitimacy and authenticity of the digital signature, a reliable intermediary can efficiently handle the conflict between them (Rivest et al., 1978). Currently, research on digital signatures primarily centers on the investigation of digital signatures based on public key cryptosystems. Rivest and colleagues introduced a digital signature plan using the RSA public key algorithm in 1978 (Bodasingi & Gunupuru, 2023), and ELGamal introduced a digital signature plan founded on discrete logarithms in 1985 (Anjaneyulu, 2022). As the current public-key cryptography framework relies on the mathematical processing of one-way hash functions, its processing speed is exceedingly sluggish so it is not feasible to encrypt the whole message text directly by public-key cryptography algorithm in practical application scenarios (Imam et al., 2021). To improve this problem, a fixed-size feature value is extracted from the message text by preprocessing the message text to be signed, which can uniquely represent the message i.e. the message digest. The message digest has the following properties: 1) every minor alteration in the message content will lead to a substantial modification in the message digest, 2) it is not practical to try to recover and obtain the original message text from the message digest, 3) it is not possible to discover two message texts with the same digest value in the computation.

In the present age of massive data, users' data information is often exposed to the risk of privacy leakage, so how to effectively avoid data leakage has become a common problem for the whole society. In the Internet era, especially in the cloud computing setting, cloud service providers and users consume too much computing resources for privacy protection, and to address this issue, homomorphic encryption (Homomorphic Encryption) technology has emerged (Wood et al., 2020). The notion of homomorphic encryption was introduced by Rivest and others in 1978 (Geng, 2019), which is an encryption scheme for direct manipulation of ciphertext (Zhang et al., 2023). The fundamental concept of homomorphic encryption is to execute a particular computation on the encrypted information in the absence of the secret key, such that the outcome of decrypting the encrypted data, after computation, matches the result of conducting the same computation on the plaintext (H. Fang & Qian, 2021), that is, homomorphic encryption can achieve an effect (Gong et al., 2023): a specific algebraic algorithm for the plaintext is equivalent to the same algebraic algorithm for the ciphertext equivalence. By this property, the operation can be performed directly on the plaintext without the need to decrypt the plaintext first and then perform the relevant operation

Zero-Knowledge Proof (ZKP) was suggested by Goldwasser and others in 1985 and refers to the ability of one party (the verifier) to believe that the assertion made by the prover is valid and correct when the other party (the prover) does not provide any reliable information, thus well protecting the privacy of the data information of the prover (Tyagi & Kathuria, 2022). This protects the privacy of the provers' data and information. Zero-knowledge proofs have the following properties: Initially, entirety, if the assertion is correct, a sincere demonstrator can convince an honest authenticator of the correctness with a significantly high probability; Second, soundness, if the claim is untrue, a dishonest prover can only persuade an honest verifier of the validity with an extremely small likelihood; and finally, zero-knowledge, after the procedure of zero-knowledge proof is executed. Following the conclusion of the zero-knowledge proof procedure, the verifier can solely acquire the knowledge that "the prover possesses this information," without gaining any specifics about the actual knowledge. (Wang et al., 2020) .

Distributed Ledger Technology and Intelligent Agreements

An automated agreement on the distributed ledger is a functional application in a contained environment (Bhardwaj et al., 2021). Unlike traditional programs, smart contracts place more emphasis on transactions and are themselves transaction-generating programs (Efimova et al., 2021). The entries, exits, and state transitions of an intelligent agreement can be found in the distributed ledger, implying that they must be carried out using collaborative algorithms among nodes. Nevertheless, an intelligent agreement is simply a component for handling transactions and documenting states. It lacks the capability to produce or revise intelligent agreements, but is limited to automatically executing agreement conditions based on predetermined parameters. Functions that can be triggered by conditions can be executed exactly as the caller wishes, realizing the goal of "code as law". Intelligent agreements conceal the complex actions of every point in the blockchain network, utilizing agreement and network encapsulation. Simultaneously, they offer an interface to the blockchain application layer, rendering the application of blockchain technology highly promising (Wang et al., 2019). Intelligent agreements are also a crucial aspect of distributed ledgers, demonstrating that distributed ledgers are not solely a digital currency, but also a distributed ledger service. Intelligent agreements empower distributed ledgers to support programmable applications, operate decentralized applications, and establish collaborative ecosystems that necessitate confidence (Leng et al., 2020).

Operating Principle

In cryptocurrencies, a smart contract-like function is to verify that the signature in the transaction is correct: to verify that the input and output amounts of the transaction match, and update the balance status of the input and output accounts (Hu et al., 2021). Regarding BTC, for example, the transfer function is implemented through a stacked scripting language that performs the above operations with less than 200 commands (Cohney & Hoffman, 2020). Inspired by cryptocurrency scripting languages, smart contracts of blockchain systems with Turing-complete operating environments usually define contracts that contain several initial states, transition regulations, activation criteria, and associated functions. These agreements are published to the distributed ledger by submitting transactions for placement on the distributed ledger following a collaborative algorithm. The distributed ledger can track the condition of the complete intelligent agreement in real time (Chang et al., 2019). When a new transaction meets certain conditions, the execution of the corresponding terms of the contract will be triggered, and after the new transaction has gone through the consensus, the inputs and outputs of the transaction within the contract and the change of status will be recorded on the blockchain. External accounts can only send messages in the form of transactions, thus creating transactions. A transaction can be a normal transaction, a contract creation or a contract invocation. If the transaction is to create a contract, a contract account is created. If the transaction is to invoke a contract, the corresponding contract terms i.e. the code, are activated and executed, and changes in the code's operations on state are recorded on the blockchain (Temte, 2019). An outside software must call the intelligent agreement, for instance, a distributed application, and conduct dealings and retrieve state information based on the agreement. The linkage between external applications and intelligent agreements can be likened to the connection between customary database applications and stored routines (Wang et al., 2019). The saved function operates in a database management system and connects with relational database information, whereas the intelligent agreement operates in a distributed ledger system and connects with blocks and state information, and the bond between the two is still waiting to be enhanced and expanded. Figure 2.7 illustrates the operational mechanism of smart contracts.

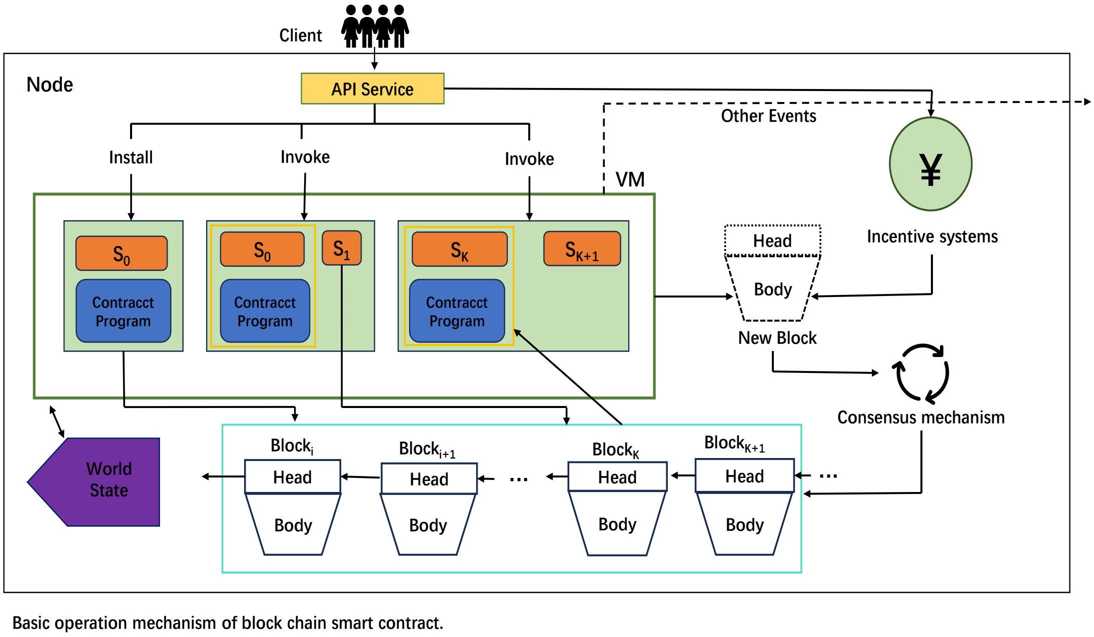

Figure 2.7 Illustrates the operational mechanism of smart contracts

Operating environment

Intelligent agreements are not executed directly in a context recognized by the distributed ledger nodes. Because direct manipulation of the blockchain's contract code, especially writing to the blockchain's data, can cause the contract to go out of control (Jawdhari & Abdullah, 2021). Compromising the data framework of the distributed ledger jeopardizes the security of the blockchain node, therefore, intelligent agreements need to operate within a contained sandbox setting (Wu et al., 2022). As a result, intelligent agreements need to operate within a separate sandbox setting. This sandbox environment effectively isolates the association between the operational environment of the agreement and the hosting system, and between the agreement and the agreement itself, which is in line with the decoupling design and enhances the security of the smart contract. Currently, the sandbox support of mainstream blockchain platforms mainly includes virtual machines and containers, which can effectively ensure the independent execution of contract code in the sandbox (Wu et al., 2022). Hyperledger Fabric adopts lightweight Docker containers as the sandbox (Honar Pajooh et al., 2021), and Docker containers are often used in engineering to provide an isolated Linux runtime environment, which can also effectively isolate the contract environment, the host environment and the contract code. Hyperledger Fabric uses lightweight Docker containers as a sandbox (Tong & Qiu, 2023). It is important to note that contracts in Hyperledger Fabric using Docker containers still have access to the Internet, whereas EVMs do not have a network interface. Smart contracts in the Ethernet environment are implemented using a high-level programming language (T. Ma, 2023). In the solidity programming language, the contract keyword defines a contract, which consists of a set of code and data, with rules for sharing contract data set by the contract author. In the following code, simple storage is a contract, stored data is a field in the contract, and the set and get functions specify that the stored data field in the contract can be read and modified by anyone on the blockchain (Mezquita et al., 2019).

```
contract Simple Storage {
        uint stored Data;
        function set( uint x) {
             stored Data = x;
             }
             function get ( ) constant returns ( uint ret Val) {
                     return stored Data;
                     }
                 }
```

In Ethernet, the contracts corresponding to the solidity language will be compiled into binary bytecode as input to the Ethernet virtual machine, which keeps the smart contracts and exposes the corresponding call interfaces of the contracts according to the sandbox mechanism (Wu et al., 2022).

2.2 Theoretical Framework

2.2.1 Efficient market hypothesis

Capital market effectiveness relates to the extent of effectiveness of the capital market in optimizing the distribution of resources to capital. First, the capital market provides capital resources to demanders and reduces transaction costs in the transaction process. The second is what level of efficient supply can be provided to the society by the demanders of capital resources after receiving the capital resources. In the scenario that the capital market performs at an improved level, those seeking capital resources will receive a restricted quantity of capital resources to ensure the maximization of the value realization for the entire market. Many theories within the field of financial economics are closely related to capital market efficiency, such as value valuation theory, portfolio theory, and capital structure theory etc. These theories are rooted in the idea that capital markets are efficient (Fama, 1970a). Observed that stock price fluctuations are stochastic and that the stock price is constantly changing in response to new information (Fama, 1970a) The effective market theory is postulated, indicating that a market is effective if alterations in the data individuals receive in the equity market are entirely manifested by the stock value. The effective market theory is categorized into three forms: the feeble effective market theory, the semi-potent effective market theory, and the robust effective market theory, based on stock values and the degree of availability of information.

The confirmation of the effective market theory for digital currencies centers on three concerns: whether yields exhibit a regular distribution, studies on volatility of information, and studies on the authenticity of information (Tiwari et al., 2018; Zargar & Kumar, 2019a) . The findings of the research do not corroborate the efficient market theory for the digital currency market. Most results confirm virtual currency market ineffectiveness Weak Efficient Market Hypothesis (Latif et al., 2017) or the semi-strong efficient market hypothesis (Vidal-Tomás & Ibañez, 2018). The relevant definition from the efficient market illustrates that prices can be reflected from the change of information, but other excess information is not possible to obtain from the trading of information. Empirical studies, however, have identified different issues from efficient markets, such as predictability of stock returns, cyclical effects etc., from which we cannot currently explain with the hypothesis of efficient markets.

There are two views on whether the virtual currency market is valid: one view is that the virtual currency market is ineffective. For example, BTC has been proven to have information invalidity (Zargar & Kumar, 2019b). Because of BTC market ineffectiveness, its price is predictable (Caporale & Plastun, 2019). As liquidity increases, virtual digital currencies become less predictable and less effective (Brauneis & Mestel, 2018). The main manifestation of BTC market ineffectiveness is the persistent asymmetry in its yields and high volatility (Brauneis & Mestel, 2018). Because of the extended-term memory characteristics of the BTC market, it is comparatively less effective compared to the Gold, equity, and forex markets. Vis-à-vis the correlation between price and trading quantity, the BTC market lacks legitimacy and exhibits an unconventional connection between fluctuations in price and fluctuations in trading volume (Aharon & Qadan, 2019). There is an intra-week effect in the virtual currency market, again illustrating market ineffectiveness, with relatively high yields on Mondays and low trading volumes on weekends (Aharon & Qadan, 2019). An alternative perspective posits that the virtual currency market aligns with the efficient market hypothesis.

The price fluctuations of BTC are unrelated to other digital currencies and do not impact or are impacted by the prices of other virtual digital currencies (Zięba et al., 2019). There exists a noteworthy correlation between BTC returns and its trading volume (Koutmos, 2018). The connection between BTC's price and trading volume follows a non-linear pattern, but the volatility of BTC returns does not serve as an indicator for predicting its trading volume. BTC shares similar attributes with conventional financial assets (e.g. stocks, bonds and currencies). However, the traditional speculative factors in traditional financial markets have restricted ability to forecast BTC prices (Aharon & Qadan, 2019; Baur et al., 2019). Current judgments on whether virtual currency markets are efficient are all based on predictions of whether virtual currency markets are different. In terms of forecasting cryptocurrency prices, virtual currency markets completely deviate from the efficient market hypothesis. Nevertheless, research has also verified that virtual currency markets still demonstrate market legitimacy under specific circumstances.

2.2.2 Random walk theory

The Effective Market Theory (EMT) asserts that in a securities market, the value of a security encompasses all the data linked to the value of the stock, and that the data influencing the alteration in the value of the security is produced haphazardly, causing the security's value to fluctuate randomly and without specific patterns (Malkiel, 1989). Any attempt to find "price-distorting" stocks through fundamental and technical analysis would be a waste of time. The economist Gibson (1889) first described the idea of efficient markets (there was no such thing as an "efficient market" at the time) within the equity markets of London, Paris, and New York, and it had some impact (Al Hamdooni, 2023). In 1900, Bachelier described and tested the random walk model in his doctoral dissertation "Speculative Theory", which argued that market trading follows a "fair" principle and that no one can profit from it, and proposed for the first time the idea that market returns follow independent identical distributions (Benjana & Yamani, 2022). Because this idea was not in line with traditional knowledge and lacked empirical evidence, it did not attract enough attention in academic circles. It was not until Working (1934) and Cowles 3rd and Jones (1937) analyzed the stock and commodity prices and found that the serial correlation between the pre and post price changes of both stocks and commodities tended to be zero, which could be depicted by the random walk model (Working, 1974). Due to the low level of development of electronic technology, the above studies lacked empirical tests, which limited the development of the correlation theory. Kendall and Hill (1953) used computers to perform large-scale calculations to analyze stock and commodity prices in the United Kingdom and found that the randomness of prices varied significantly over time in a time series, with random walk characteristics. This discovery impacted the prevailing theories of fundamental and technical analysis and given the foundation for the creation of the effective market theory. Since then, there has been an abundance of research in this domain. In his examination of the U.S. equity market, Osborne (1959) found that the fluctuation of equity values was quite akin to Brownian motion in that it was arbitrary and that the logarithms of price shifts were unconnected to each other. Drawn from the random walk concept, the effective market theory was additionally elaborated by (Samuelson, 1965) who, after studying the random walk theory, revealed the "arm's length" principle in the EMH expected return model. Fama (1970b) described an effective market as one in which the value of a security appropriately reacts to all accessible data and promptly responds to new information. In an efficient market, any attempt to find "price-distorting" stocks through fundamental and technical analysis would be a waste of time. Malkiel and Malkiel (1973) famously conducted an investment competition between experts and monkeys in "Walking on Wall Street". The experiment found that a randomly selected portfolio of monkeys performed as well as a carefully selected portfolio of experts. In 1992, Malkiel showed that a market is efficient if its price adequately responds to all information; In an effective market, investors are unable to leverage information asymmetry to generate supplementary returns (Malkiel, 2003). Imagine an efficient market in which each investor has the same information and the same prediction of the market price. Then, only when the price is equal to the predicted value, can the two sides of the transaction reach a deal. At this point, the transaction is "arm's length" and the market price fully reflects all information. However, investors cannot expect good or bad market information in the future, and good news and bad news are random, so market price fluctuations are random and unpredictable (Veronesi, 1999).

The Random Walk Theory is a financial concept suggesting that the values of financial assets, such as stocks and cryptocurrencies like BTC, follow a random and unpredictable path. In the situation of BTC investment, the theory presumes that the BTC market is effective, indicating that all accessible data is already integrated in the value of the asset. As a result, investors cannot gain a sustained advantage by analyzing historical price data or utilizing tools for technical analysis to forecast upcoming price shifts. Since the theory implies that BTC price movements are random and independent of each other, this suggests that any predicted price trends could be coincidental and not reflect actual patterns. This unpredictability makes it challenging for investors to determine the best entry and exit points for BTC investments. In the case of BTC investing, this suggests that holding cryptocurrencies for an extended duration could yield similar results as trading cryptocurrencies frequently adhering to market circumstances. It is noteworthy that although the theory of random walks has garnered some acknowledgment among financial analysts and scholars, it remains a topic of debate, and many investors continue to use a variety of methods, including technical analysis, to predict and capitalize on price trends in the BTC market. As with any investment, participants should conduct thorough research and consider their risk tolerance before entering the volatile world of cryptocurrency investing.

2.2.3 Stock price mean reversion theory

For many years, the matter of stock price predictability has drawn the interest of numerous market practitioners and scholars in 1959. Shiller (2003) saw the advancement of stock price predictability research through the theories of Robes, who provided the argument that continuous price changes should be characterized as independent, and obviously, who advanced the proposition that the independent variable is not the actual price change, but the logarithmic price change (Saari, 1976). Under the assumption that the logarithmic variation itself is normally distributed, it implies that prices are generated by Brownian motion. Many practical tests have also indicated that future stock price patterns can be anticipated according to previous stock price shifts, that is, stock prices do not conform to the random walk pattern and exhibit varying degrees of autocorrelation. In the recent past, mean reversion theory has posed the greatest challenge to random walk theory. From its inception, the theory of portfolio investment has been a theory of how to predict stock prices. Fama and French (1988) initially determined that equity returns tend to revert to the mean over extended periods, following an empirical analysis of the stock exchange in New York, USA. Balvers et al. (2000) suggest that equity returns regress toward the mean over extended periods in seven stock markets in Southeast Asia and 18 stock markets in developed nations across Europe and the United States. The study of mean reversion theory undoubtedly provides an important theoretical reference for long term investors and is a milestone for the theory of equity investment. We comment on the mean reversion theory in the following aspects: 1) Mean reversion should be theoretically unavoidable (Pellegrino, 2021). As it is definite, equity prices cannot perpetually rise or fall, and a pattern cannot endure indefinitely, regardless of its duration. Within a trend, the stock price is continuously rising or falling, which we call Mean Aversion (Filiz et al., 2021). Mean Reversion occurs when there is an opposite trend. So far, what the mean reversion theory cannot solve or predict is the time interval of the reversion i.e. the period of the reversion is a "random walk". The duration of regression differs from one stock market to another, and even for the same stock market, the duration of regression changes from time to time. If the time span of mean reversion or the scope of the distribution of the reversion time span can be identified, the predictability of stock returns will be high. Otherwise, it is still meaningless to simply prove the existence of mean reversion in a given stock market. It seems that the study of mean reversion theory is only in its infancy, and there is much to be done in the future. 2) Mean reversion is necessarily asymmetric (Mair & Thoma, 2019). The size and velocity of the decline in favorable returns and unfavorable returns may not be identical. As they are not inherently linked, the scale and pace of decline are also arbitrary. It is the symmetric mean reversion that is abnormal and contingent, as confirmed by empirical tests. 3) Mean reversion theory and government behavior (Corbet & Katsiampa, 2020). The mean reversion of stock returns proves that the market does not deviate from the value pivot for too long and that the market's internal forces drive it back to its intrinsic value. In this regard, the market will achieve its objective effectively in the absence of positive or negative government policies i.e. stock prices will naturally revert to their mean value due to the market mechanism (Agarwal et al., 2019). However, this does not negate the role of government action in promoting market efficiency, as market divergences from inherent worth do not instantaneously trigger a return to inherent worth, it is probable that there will be sustained mean reversion. Regulatory intervention can contribute to quelling market inefficiency and fostering market efficiency. Government intervention is a pivotal element in advancing market efficiency, and market inadequacy is a direct cause for government participation in regulation.

When it comes to BTC, the same theory can apply. BTC is a volatile asset whose price can deviate significantly from the mean. The theory of mean reversion suggests that if BTC's price deviates significantly from its mean, it is probable that it will eventually return to the average. Nonetheless, it is crucial to acknowledge that BTC is a comparatively recent asset category in comparison to conventional stocks, and it operates in a distinct market setting. The factors that drive the price of BTC are different from those that affect traditional stocks, as BTC is influenced by factors such as market sentiment, regulatory developments, technological advances, and overall demand and adoption. Therefore, while mean reversion theory can provide some insight into the potential movement of BTC's price, it should be used with caution. The price of BTC is also impacted by additional elements unique to the crypto market that could add to its intrinsic instability and price fluctuation.

2.2.4 Value Investing Theory

The concept of value investing Benjamin Graham mentioned the concept of value investing in his completed book "Security Analysis" and used the term intrinsic value again, so value investing theory can be called intrinsic value theory (Greenwald et al., 2020). The definition of value investing by scholars has produced some differences in form, but its inner principles have not changed significantly. The distinctive views on the definition of value investing can be broadly divided into Graham's theory and Fisher's theory (Pan, 2021). Among them, Graham believes that the value of a security is the value measured by facts, which include not only the income of the company, the amount of assets, and the distribution of dividends, but also all the expected future earnings that are determined (Ball et al., 2020). By assessing the inherent worth of a share, guided by these metrics, and subsequently picking equities with a low quotient of share price to share value, the investor will be able to earn more than the average increase in the stock market when the price converges to its value.

In general, Graham is more concerned with the calculation of tangible assets of listed companies and less concerned with intangible assets such as patents, brand names and reputation (Greenwald et al., 2020). Hart (1989) believed that excess profits could be obtained by investing in companies with superior profitability and by partnering with capable managers. He looks at the future viability of public companies and judges them by focusing on factors that add value to the company. Fisher believes that value is a special attribute of a company, and that this "value" characteristic enables the company to increase its profits year after year i.e. the company has outstanding profitability (Gayam et al., 2021). Combining the two typical value investment views, we can conclude that the connotation of value investment theory includes the following three points: First, While there are different interpretations of worth concerning value investments, there is no doubt that value is obtained based on the characteristics of the listed company itself, whether in terms of tangible earnings level, asset amount, dividend distribution, or intangible excellent operational management, profitability, or expectations of the future (Zuhroh, 2019). The future expectations are derived from the listed company itself. Second, the stock price always fluctuates according to the inherent value of the stock. Although the inherent value of the company remains relatively stable, the stock price is constantly fluctuating up and down according to the value, and based on this principle, the stock price will gradually approach the value according to the inherent adjustment mechanism of the stock market. When a stock is purchased at a price below its intrinsic value and sold when the value returns, the investor can earn excess returns. Third, the value investment method is to determine the appropriate investment target by studying the fundamental conditions of each listed company that investors are concerned about and by making comparisons (Sukhari & De Villiers, 2019). The investor's ability to grasp the current state of the market and personal qualities are the key to distinguish the quality of value investment, not the length of holding time.

In conclusion, value investing is an investment philosophy and approach rooted in thorough examination of the financial condition of publicly traded firms, utilizing a robust model for calculating inherent value, and opting for companies whose market value is beneath their intrinsic value for investment (Greenwald et al., 2020). Value investing is the study of fundamental information about a company, including but not limited to its financial condition, and safe investment is based on detailed knowledge of the financial status of the prospective investment corporation. The intrinsic value of a stock can be measured and expressed as a number, and the price of a stock always fluctuates according to the intrinsic value. Hence, when the value of a share is reduced in comparison to its inherent worth, it presents an investment prospect for the investor.

Value Investing Approach

Derived from the previously mentioned notion of value investing, the method of value investing can be condensed into the subsequent process (Mikalef et al., 2019): First the value investor needs to identify the target company and then conduct sufficient research on its fundamental information to evaluate the inherent worth of the company and contrast it with the existing price provided in the market. When the price is lower than the value, investors in the market buy the security. After summarizing and outlining, the evaluation process can be divided into 4 steps as follows:

1) Select the security to be valued according to your intention.

2) Understand the financial situation of the company in detail through the company's published information and market evaluation.

3) Estimate the intrinsic value of the security through a valuation model.

4) Compare the stock assessment with the market price to determine whether to buy or sell the security.

Principles of Intrinsic Value Modeling

(1) Investment Principles

When making an intrinsic value investment choice, investors are much more concerned with profits than with assets. Thus, the profit component is crucial in shaping the determination (Weixiang et al., 2022). Due to this profit-centric role, the determination of a stock's value is increasingly influenced by earnings performance, which is judged on the basis of a test of profitability rather than on the basis of a dual value test provided by both earnings power and asset factors, which results in a one-sided and unreliable judgment. An experienced investor who has analyzed a large amount of stock data can see that it may be easier to fall into the wrong conclusion by studying only the earnings statement than by studying only the balance sheet, and that the earnings statement is often presented in a misleading reporting format (D. Zhang & Lou, 2021). While recognizing the importance of profitability, it is vital to acknowledge that the worth of a company's assets bears importance for investment choices. Therefore, when modeling intrinsic value, we should fully consider whether the model can include information on both profitability and asset factors, and the resulting model should be convenient for investors to make investment decisions (Wu et al., 2022).

(2) Principle of combining qualitative and quantitative analysis

When analyzing a company, the analysis of qualitative factors of the company should be the focus, but it is difficult to measure (Namugenyi et al., 2019). Qualitative analysis belongs to evaluating qualitative aspects of a company in value assessment, and typical company value analysis reports devote most of their time to the presentation of figures, while the qualitative aspects are too concise and general. In the qualitative analysis of a company, the focus is on the following five aspects: 1) the characteristics of the industry in which the company functions 2) the company's position within this industry 3) the geographical location of the company 4) the business style and operation of the company 5) the development prospects of the company and the industry to which it belongs. It is much easier to analyze the quantitative factors of a company than the qualitative factors, because the quantitative factors are expressed in specific figures and limited in number, which are relatively easy to obtain and can be studied and processed by data or even simulated to reach clearer and relatively reliable conclusions (Mau, 2019). In order to reasonably examine the true strength of a company, it is necessary to analyze the company's operating data in conjunction with its financial statements and, if necessary, to process the data in order to draw qualitative conclusions from them. Therefore, to ascertain the worth of the stock in a more rational manner, it is essential to develop a valuation framework that encompasses both qualitative and quantitative data regarding the company. The valuation model incorporates as many factors as possible by considering the company's fundamentals in a holistic manner and fully exploring the real performance information of the listed company (Palepu et al., 2020).

Prerequisite Assumptions of The Model

In practice, there are many constraints that make it difficult to assess the inherent worth of an organization. First, the stock market is weakly efficient (K. Khan et al., 2020). Through the continuous arbitrage operations of investors and the automatic regulation of the market, the price of a stock may deviate from its true value for a short period of time, but its price and value will gradually reach equilibrium. Second, the overall level of welfare and wealth accumulation in a country will continue to increase (Chancel et al., 2022), and the increase will be reflected in the growth of resources and profitability of some of the more important firms through the normal process of investing additional capital and reinvesting undistributed earnings. It is also assumed that the stock market will remain relatively stable for a considerable period of time, without significant fluctuations due to systemic risks. These assumptions indicate that the choice of investment in common stock is not an arbitrary process, but a comprehensive study of the company's operating data in conjunction with the prevailing market price of the stock (Fridson & Alvarez, 2022). If these assumptions exist, the estimated intrinsic value of the stock will have a high validity and will provide greater investment opportunities, and when the market is stable, the investment opportunities obtained through rational analysis will prevent the investor's investment behavior from being disturbed by instability. With these assumptions, the intrinsic stock value valuation model will be effective in assessing the true value of a company's stock.

It's noteworthy that BTC's attributes set it apart from typical value investment prospects. BTC is an exceedingly speculative and unstable asset, subject to regulatory uncertainties, technological risks, and market sentiment. These factors can introduce significant volatility and make it difficult to apply traditional value investing principles with the same level of certainty. As the understanding and acceptance of BTC as an asset class evolve, new valuation models and investment theories specific to cryptocurrencies may emerge, providing more refined approaches to assessing BTC's value and investment potential.

2.2.5 Diversification Theory

Portfolio diversification is a significant theory in the realm of investment administration., which advocates the construction of diversified portfolios to reduce risk and increase investment returns (Hill, 2020). Its core idea is that investors should not put all their funds into one or a few types of assets, but should evenly allocate their funds to various different types of assets so that when some investments perform poorly, other investment gains can make up for the losses, and ultimately achieve a stable growth in overall investment returns.

The theory of diversification can be traced back to as early as 1952, when American economist Harry Markowitz proposed the Modern Portfolio Theory (MPT) in his book Portfolio Selection, which describes the principles and methods of diversified investment (Francis & Kim, 2013). According to Markowitz's theory, there are two main sources of risk in an investment portfolio: price fluctuations between individual assets (i.e. individual risk), and price fluctuations in the market as a whole (i.e. systemic risk). Through diversification, investors can reduce individual risk, but systemic risk cannot be eliminated.

In order to achieve diversification, investors can choose from the following: 1) Diversifying across asset classes involves investing capital in a range of asset categories, including equities, fixed income securities, cash equivalents, commodities, real estate, and more, to mitigate the risk associated with a solitary asset category. 2) Geographic diversification: allocate funds across domestic and global markets to mitigate the risks associated with geopolitical and economic factors. 3) Sectoral diversification: invest funds in stocks and bonds in different industries, to reduce the risk of fluctuations in industry cycles. 4) Diversification by industry: Investing funds in stocks and bonds of different industries reduces the risk of industry cycle fluctuations. 5) Diversification by company: Investing funds in stocks and bonds of multiple companies reduces the business risk of a single company.6) Diversification by investment strategy: Investing using different investment strategies (e.g., value, growth, indices, etc.) improves the stability of returns.

In contradistinction to traditional assets (like stocks, bonds, cash, commodities, real estate, etc.), BTC has unique risk and return characteristics, thus, it can be employed as an element of an investment portfolio within the context of diversification theory, helping to achieve a reduction in investment risk and a steady increase in returns. The main advantages of including BTC in a diversified portfolio are as follows: 1) Risk diversification: The BTC market has relatively low correlation with other traditional asset markets. This suggests that fluctuations in the value of BTC are less correlated with changes in the value of other assets. Consequently, incorporating BTC into a portfolio mitigates the overall risk of the portfolio. 2) Potential for Yield: Over the last few years, the value of BTC has demonstrated volatility and has predominantly displayed an ascending trajectory, providing investors with significant gains. While past returns do not guarantee future performance, the inclusion of BTC may contribute to an elevation in overall portfolio return expectations.

However, there are certain risks associated with including BTC in a portfolio: 1) High volatility: The value of BTC is extremely prone to volatility, and over-investment in BTC may result in losses from asset volatility for investors with a low risk tolerance. 2) Regulatory risk: The regulatory environment facing digital currencies such as BTC remains volatile and may face regulatory bans or restrictions in a number of countries and regions, which will affect the liquidity and price of BTC. 3) Technology Risk: Although blockchain technology is considered secure, it may still face risks such as hacking and 51% attacks, which, in turn, could impact the stability of the BTC market.

In view of the characteristics and potential risks of BTC, investors need to carefully assess their own risk tolerance, appropriately control the investment ratio and avoid over-concentration when incorporating it into a diversified investment portfolio. In practice, some financial institutions and investors have begun to include BTC or other digital currencies in their asset allocations and adjust their investment strategies in a timely manner according to market changes.

Ultimately, the relationship between diversity theory and BTC highlights the potential benefits of diversifying an investment portfolio to include different asset classes. However, due to BTC's unique characteristics and risks, investors should thoroughly evaluate their capacity for risk and investment goals before making choices regarding portfolio diversification.

2.3 Related Work about BTC

BTC is a digital communication protocol enabling the use of virtual currencies for electronic transactions. Since its establishment in 2009, it has become clear that the acceptance of the BTC payment system has significantly risen. The domain of virtual currencies has expanded immensely in terms of user base, variety of cryptocurrencies, and frequency of transactions. BTC's expansion has led investors and stakeholders to view virtual currencies as a groundbreaking asset class with investment potential. Numerous studies have investigated and underscored the connections between BTC and GOLD, Petroleum, and the American currency, attracting close attention from economists, policymakers, and business leaders. The central discussion in the literature revolves around the nature of the relationship between BTC and GOLD, Petroleum, and the U.S. dollar, as well as the implications for investment in light of the altered dynamics due to the COVID-19 pandemic.

2.3.1 Relationship Between BTC and Financial Assets

Examination of the correlation between BTC and financial assets has mainly focused on the recent period, and an examination of available articles indicates that the association between the two elements has not led to a more unified verdict, making it a key area of interest for the academic community.

Briere et al. (2015) explored the connection between BTC and conventional assets (worldwide stock index, fixed-income securities, government-issued currencies) as well as unconventional assets (raw materials, alternative investment funds, physical property) within the context of varied investment portfolios. The research revealed that the correlation between BTC and other assets was extremely minimal. This indicates that the price fluctuations of BTC are not strongly connected to those of other assets, implying that BTC may provide distinctive diversification advantages for investors.

Corbet et al. (2018) explored the correlation between three presently utilized cryptocurrencies and alternative financial assets, including stocks, precious metals, and fixed-income securities. The research revealed a significant level of interrelation among cryptocurrencies, whereas the connection between BTC and prominent financial assets was comparatively distinct. Nonetheless, the analysis also uncovered that the association between BTC and mainstream financial assets, such as equities, precious metals, and fixed-income securities, was relatively distinct. This implies that the price fluctuations of BTC are not firmly impacted by or associated with the fluctuations of these conventional assets.

Baur et al. (2018) similarly deduced through regression analysis that the return on BTC was not correlated with traditional financial asset categories, such as stocks, fixed-income securities, and raw materials, either in regular periods or amid financial upheaval. Their findings suggest that the returns on BTC do not move in tandem with the returns of traditional asset classes, regardless of the market conditions. This implies that BTC may have a unique set of drivers and factors that influence its price movements, which are distinct from those affecting traditional financial assets.

G. Wang and Hausken (2022) studied the hedging capacity of BTC against six assets, including global stock index, fixed-income security, crude petroleum, precious metal, raw material index, and American money index, through employing the binary DCC-GARCH approach, and observed that BTC can efficiently spread the investment hazard in the majority of scenarios, however BTC provides a hedge impact in very limited instances.

Ji et al.(2018) explored the interconnectedness of BTC value and traditional financial factors via VAR and ECM techniques and utilized a directed acyclic graph to unveil the present and delayed interaction between BTC and alternative asset categories. The results of the concurrent analysis suggest that the BTC market is relatively isolated, with no single asset exhibiting a predominant role in the BTC market. Yet, findings from academics indicate that the cause-and-effect connection fluctuates over time, and there is a postponed connection between BTC and specific assets, particularly when the BTC is experiencing a downturn in the market.

Bouri et al. (2018) utilized the binary STVAR-GARCH-in-Mean model to examine the profit and volatility premium connection between BTC and four resources, specifically, stocks, raw materials, foreign exchange, and fixed income securities in favorable and negative market conditions, and discovered that BTC is strongly connected to the return of the majority of resources, particularly the raw material index. This suggests that BTC displays a greater level of correlation with raw materials, particularly the commodity index, in contrast to alternative asset categories. The resemblance in the association between BTC and raw materials, including precious metal, is significant.

Klein et al. (2018) employed a dual BEKK-GARCH model to assess the time-varying conditional association between BTC and Gold and the equity market separately, and discovered that in the declining market, notably in 2015, BTC was favorably connected with the S&P 500 Index, whereas Gold was unfavorably connected with the S&P 500 Index, and the two interrelations displayed a trend to travel in the reverse direction. The findings of the analysis demonstrate that BTC was favorably linked with the S&P 500 during the declining market, particularly in 2015. This implies that BTC and the equity market moved in comparable directions throughout this time frame, indicating a prospective favorable association between the two.

Othman et al. (2019) analyzed the volatility of BTC, US dollar and Gold by using GARCH and E-GARCH models and introducing asymmetric terms, and found that BTC and Gold have similar hedging ability and similarity with the US dollar as their returns are less affected by short-term price shocks. Their findings suggest that BTC and Gold exhibit similar hedging abilities. This indicates that both BTC and Gold have the potential to function as safeguards against immediate price disruptions or market instability.

Chan et al. (2019) additionally examined the hedging capability of BTC and discovered that BTC possesses the capability to mitigate risk against the equity index and American currency in the near future. The results indicate that over a brief period, BTC has the capacity to function as a safeguard against stock indices and the U.S. dollar. This indicates that the returns of BTC may exhibit a negative correlation or offer a level of defense against fluctuations in the valuation of the equity market and the United States dollar for a relatively limited duration.

Kyriazis et al. (2019) using the same sample as Dyhrberg, obtained the exact opposite results, establishing that BTC differs significantly from Gold and government-issued currencies, follows a different volatility profile than other assets, and is not correlated. This study found that BTC, unlike Gold and fiat currencies, is not correlated with these assets. The study also concluded that BTC has a different volatility profile compared to other assets. These findings suggest that BTC may offer diversification benefits and may exhibit independence from traditional assets. However, further research and analysis is needed to fully understand BTC's relationship with other assets and its potential dynamics.

Gustafsson et al. (2022) utilized the DCC model to analyze the connection between energy and non-energy goods and BTC values. This investigation determined that there existed a feeble favorable association between BTC values and energy values. Employing an irregular multivariate VAR-BEKK-GARCH model.

Kahyaoğlu et al. (2020) carried out a pertinent research on Turkey to aid investors, legislators, and oversight organizations and others to gain improved insight into the function of BTC in investment within the Turkish environment. The research intended to examine and comprehend how BTC is employed and regarded as an investment instrument in the Turkish sector.

Arfaoui and Yousaf (2022) explored the correlation between BTC and the stock indices of renewable energy, traditional fuel energy, and information technology companies. The results indicate significant one-sided profit transfers from energy and technology stock indices to BTC, with energy and technology stock benchmarks having substantial one-sided profit transfers to BTC, and energy and technology stock benchmarks having substantial one-sided profit transfers to BTC. The findings indicate that the energy and technology benchmarks have noteworthy one-directional dividend transfer impacts on the BTC, while the volatility transfer impacts of both benchmarks are reciprocal. In available literature, there have been limited studies on the relationship between BTC and traditional financial assets in specific nations or regions. Kahyaoğlu et al.(2020) performed an applicable investigation regarding Turkey to aid investors, policymakers, regulatory authorities, and others in gaining an improved comprehension of the function of BTC in investment within the Turkish setting.

(Zeng & Ahmed, 2022) applied the VAR-BEKK-GARCH model to examine the overflow influence of BTC with six financial resources in China (equities, commodity futures, precious metals, forex, currencies, and fixed-income securities), and discovered that solely currencies possess a mean overflow influence on BTC, while precious metals, currencies, and fixed-income securities all have volatility overflow influences on BTC. Precious metals, goods, and fixed-income securities all have volatility overflow influences on BTC, however, BTC solely has volatility overflow influences on precious metals.

In a regional study on the correlation between BTC and monetary resources, (Hong et al., 2022), by applying the traditional Granger causality test, impulse impact analysis et al., conducted a malefactor study on the impacts of Gold, petroleum prices, foreign exchange, stock indices, and interest rates on the price of BTC.

(Kumar et al., 2023) discovered that fluctuations in the values of precious metals and crude oil have a substantial and favorable influence on the value of BTC. Employing the vector autoregression-Baba Engel Kraft Kroner-generalized autoregressive conditional heteroskedasticity model. Li Jing and (Zeng & Ahmed, 2022) found that the BTC market in China and the US had a two-way spillover effect, but the spillover effect from China to the US market was significantly stronger.

2.3.2 Cryptocurrency Price Prediction Problem

There are many approaches to the price prediction problem. Many authors have used several prediction methods, including conventional models and computational intelligence models, to forecast BTC price or BTC returns.

Muhammad et al. (2021) built predictive models based on Naive Bayes. However, the authors recognized that Naive Bayes' key disadvantage is that separate predictors are presumed. Many independent predictors are almost impossible to obtain, and if the variable has an unreported category in the test data set, then the model assigns a zero likelihood and cannot predict the price. The Laplace estimate is one of the most straightforward smoothing techniques.

Khedr et al. (2021) used Bayesian Regression to forecast BTC's price fluctuations and build a profitable trading strategy for cryptocurrencies. Their approach can almost double the investment in a BTC portfolio in less than 60 days when working against actual cryptocurrency exchange trading results. Their process does not determine how to pick a previous analysis, and the best way to select a prior is not available because Bayesian inferences require the expertise to translate previous subjective convictions to have a good analysis mathematically. Logistic Regression examines the relationships between the variable and one or several variables that are independent. Unlike linear regression, which is sufficient for continuous variables, it uses a logistic function to estimate a categorical dependent variable's probabilities.

(Artigue & Smith, 2019) addressed logistic regression's primary limitation, which is the linearity of the dependent variable with the independent variables. It assesses the effectiveness of a predictor (coefficient magnitude) and evaluates its collective orientation (positive or negative). Some writers have employed logistic regression to predict fluctuations in the cryptocurrency market (Andi, 2021; Basher & Sadorsky, 2022; Charandabi & Kamyar, 2021; Pabuçcu et al., 2023).

Konstantinov and Utkin (2021) concluded Gradient Boosting Models (GBMs) are valuable techniques. GBMs collaborate with weak models of prediction, such as decision trees. Some research studies have used GBMs and related techniques, such as extreme gradient boosting, to estimate the proportion of cyber-criminal organizations in the BTC ecology and classify Ponzi schemes BTC environment (Derbentsev et al., 2021). Since optimizing an objective function, boosted trees are derived, it is practically feasible to apply GBM to tackle nearly all purpose functions formulated through gradients encompassing aspects such as scores and regression of venom, which is more challenging for random forest to achieve.

Dutta et al. (2020) utilize macroeconomic signals such as interest rates, S&P 500 market performance, U.S. bond yields, and the level of Gold prices as forecast variables for day-to-day BTC prices. Examination of the Extended or Brief Forecasting Potential of Macroeconomic and Blockchain Information Indicators. The findings reveal that macroeconomic indicators possess near-term forecasting capability.

Basher and Sadorsky (2022) additionally utilize macroeconomic signals, incorporating the Gold spot price measure, as forecast variables for the daily BTC price. Their findings indicate that macroeconomic indicators demonstrate immediate-term forecasting ability.

Ünvan (2021) examined the influence of macroeconomic elements on BTC values, involving the S&P500 benchmark market profits, DOW30 benchmark, NASDAQ benchmark, crude Oil, Gold, and FTSE benchmark. Their results offer factual support that the recent changes in the day-to-day value of BTC are not derived from macroeconomic signals.

Erfanian et al. (2022) explored the macroeconomic metric, supply expansion (defined as BTC in circulation), to grasp its impact on BTC gains, and they found that supply expansion is positively linked to weekly profits.

Bakas et al. (2022) revealed that the instability of the S&P 500 benchmark has a significant positive impact on the long-term volatility of BTC. The results indicate that the key factors influencing BTC volatility include Google search trends, overall circulation of BTCs, US consumer sentiment, and the S&P 500 benchmark.

Corbet et al. (2021) explored the influence of distributed ledger data (covering mean block magnitude, miners' earnings, mining complexity, and hash rate) on BTC values. Their findings provide empirical evidence that recent fluctuations in the daily price of BTC stem from blockchain information metrics.

Kobayakawa et al. (2020) explored the impact of distributed ledger data metrics, including multiple distinct contributors contributing code to the project, the count of incorporated suggestions in the primary codebase, the count of community inquiries regarding the code, and the count of offshoots with a set number of developers, on BTC profits. They observe an affirmative and noteworthy correlation between distributed ledger data measures and weekly profits. Consequently, uncertainties persist among the writers regarding whether distributed ledger data measures possess extensive or immediate-term forecasting capability.

2.3.3 Related Studies of Comparative Analysis on BTC Price Prediction

This portion showcases several investigations linked to comparative examination of the BTC price forecasting issue sorted into traditional methodologies and artificial intelligence methodologies.

Related Studies on Conventional Approaches

Othman et al. (2020) conducted a study that found BTC to have high volatility compared to traditional financial markets. This volatility can make price prediction for BTC and other cryptocurrencies more challenging. The inherently decentralized and speculative nature of cryptocurrencies, coupled with factors such as market sentiment, regulatory environment, and technological developments, can contribute to rapid and significant price fluctuations.

Celeste et al. (2020) discovered that BTC experiences remarkably strong gains in economic assessment, but its unique characteristics of heightened volatility and minimal correlation set it apart from traditional assets. In actuality, cryptocurrency trading can be viewed as a time series prediction challenge, yet cryptocurrency rates might exhibit cyclic upswings and abrupt drops within a specific timeframe. Consequently, the cryptocurrency trading community requires a standardized approach to precisely anticipate fluctuations in price trends.

Poyser (2019) primarily employed predominantly conventional financial market approaches for examination and prediction. Certain researchers have also explored utilizing econometric methodologies such as Vector Autoregression (VAR), Ordinary Least Squares (OLS), and Quartile Regression (QR) to examine the impact of economic and technological factors on the BTC exchange rate.

Duan et al. (2020) utilized traditional time series prediction methods including univariate autoregression (AR), univariate moving average (MA), simple exponential smoothing (SES), and autoregressive integrated moving average (ARIMA) methods to forecast BTC cost and volatility, respectively.

Yuan et al. (2016) contended that these approaches are not particularly efficient for this predictive task, given the absence of periodicity and the heightened instability of the cryptocurrency market, as well as the reliance on statistical models that can solely handle linear predicaments and necessitate normal distribution adherence by the variables. In recent years, artificial intelligence methodologies have been utilized for the task of predicting asset prices and profits, alongside digital currencies. Artificial intelligence methodologies have been effectively leveraged for stock market prognostication by integrating nonlinear attributes into the prognostication model to handle non-stationary financial time series, and the findings indicate that the prognostication methodology employed is more efficient (Yuan et al., 2016). The artificial intelligence approach allows us to grasp the non-linear characteristics of highly volatile cryptocurrency rates, deviating from conventional linear statistical models (ARMA). Instances of artificial intelligence investigations employed to anticipate the value of BTC encompass Bayesian neural networks and neural networks (Kasahara & Kawahara, 2016).

Wu et al. (2020) who determined that although neural networks effectively estimated the distribution of BTC's logarithmic yields, more sophisticated learning approaches like deep recurrent neural networks (RNNs) and long and brief-memory artificial neural networks (LSTMs) can produce superior prediction accuracy.

Ramadhani et al. (2018) contrasted an ARIMA chronological series model with an LSTM profound learning model to assess the forthcoming value of BTC, and discovered that the mean absolute discrepancy of the LSTM model was substantially reduced, indicating that the LSTM is more precise when utilized to prognosticate BTC's value.

Aalborg et al. (2019) Investigated the future prediction of BTC using the operations of the blockchain network and illustrated that, according to the findings, the LSTM has the ability to forecast the future value of BTC. Projections and results showed that the accuracy measure of the binary classification problem was nearly equal to or below 50%. Therefore, the algorithm based on the deployed blockchain network proved ineffective in predicting the fluctuation in BTC value.

Bouoiyour and Selmi (2015) utilized a specialized neural network founded on a genetic algorithm to examine a pattern of the association between the forecaster variables of BTC and the daily shift in BTC, which was utilized to foresee the day-ahead shift of BTC value. After acquiring the pertinent data from the BTC price index, a Bayesian optimized recurrent neural network was employed to forecast the time series data of BTC price levels. The outcomes indicate that the BNN surpasses linear regression and support vector machine models in price prediction.

There are many approaches to the price prediction problem. Many authors have used several prediction methods, including conventional models and computational intelligence models, to forecast BTC price or BTC returns. For example, Wimalagunaratne and Poravi (2018) built predictive models based on Naive Bayes. However, the authors recognized that Naive Bayes' key disadvantage is that separate predictors are presumed. Many independent predictors are almost impossible to obtain, and if the variable has an unreported category in the test data set, then the model assigns a zero likelihood and cannot predict the price. The Laplace estimate is one of the most straightforward smoothing techniques.

Khedr et al. (2021) used Bayesian Regression to forecast BTC's price fluctuations and build a profitable trading strategy for cryptocurrencies. Their approach can almost double the investment in a BTC portfolio in less than 60 days when working against actual cryptocurrency exchange trading results. Their process does not determine how to pick a previous analysis, and the best way to select a prior is not available because Bayesian inferences require the expertise to translate previous subjective convictions to have a good analysis mathematically.

Lumley et al. (2002) examines the relationships between the variable and one or several variables that are independent. Unlike linear regression, which is sufficient for continuous variables, it uses a logistic function to estimate a categorical dependent variable's probabilities. In accordance with, the primary limitation of logistic regression is the linearity of the dependent variable with the independent variables. It measures the adequacy of a predictor (coefficient size) and measures its assembly direction (positive or negative). Some authors have used logistic regression to forecast cryptocurrency market fluctuations (Ashayer, 2019; Greaves & Au, 2015; Shah & Zhang, 2014).

For both regression and classification problems, (Guo et al., 2018) concluded Gradient Boosting Models (GBMs) are valuable techniques. GBMs collaborate with weak models of prediction, such as decision trees. Some research studies have used GBMs and related techniques, such as extreme gradient boosting, to estimate the proportion of cyber-criminal organizations in the BTC ecology and classify Ponzi schemes BTC environment. Since optimizing an objective function, boosted trees are derived. It is nearly feasible to employ GBM to resolve virtually all task functions that can be articulated by gradient, encompassing elements such as rating.

2.3.4 Insights Over the Existing Literature and Current Research Work

As of now, experimental investigations do not show a clear advantage for the emerging approaches of employing machine learning algorithms to predict the BTC value, and research in this field is lacking. As a result, this investigation will contribute to highlighting the importance of machine learning approaches in BTC value prediction issues. Moreover, Digital Money Value Anticipation Issue, particular research indicates machine learning surpasses statistical assessment, while some continue to endorse the dominance of traditional statistical analysis.

Table 2.2 Overview of Research Published on BTC Price Prediction

Reference	title	Technique	Data source	findings
Carbó and Gorjón (2022)	Application of Machine Learning Models and Interpretability Techniques to Identify the Determinants of the Price of Bitcoin.	LSTM algorithm.	Coinmetrics (technological factors), Yahoo Finance (economic factors), Google (Google Trends), and Bitinfocharts (Number of Tweets).	We determine that the significance of the various factors in bitcoin value formation varies considerably throughout the analyzed duration.
Liu et al. (2021)	Forecasting the price of Bitcoin using deep learning	SDAE	'www.coindesk.com' and 'BTC.com'	The findings indicate that in comparison to the widely used machine learning techniques, such as back propagation neural network (BPNN) and support vector regression (SVR) methods, the SDAE model demonstrates superior performance in both directional and level forecasting.

Table 2.2 Overview of Research Published on BTC Price Prediction (Cont.)

Reference	title	Technique	Data source	findings
Abu Bakar et al., (2019)	Forecasting cryptocurrency price movement using moving average method: A case study of bitcoin cash	Vector error correction	Publicly	The findings might highlight the effectiveness, limitations, and potential insights gained from using this method for forecasting cryptocurrency prices, particularly within the context of Bitcoin Cash as the case study.
Akcora et al., (2018)	Forecasting bitcoin price with graph chainlets, Adv ances in knowledge discovery and data mining	k-chainlets	Bitcoin core	The findings could potentially reveal the effectiveness and accuracy of this method in forecasting Bitcoin price movements, which may be of interest to investors, financial analysts, and researchers in the cryptocurrency space.

Table 2.2 Overview of Research Published on BTC Price Prediction (Cont.)

Reference	title	Technique	Data source	findings
Alahmari (2019)	Using machine learning ARIMA to predict the price of cryptocurrencies.	ARIMA	CoinMarketCap	The results of this research are likely to offer understanding into the efficiency of merging machine learning with conventional time-series examination (ARIMA) in predicting digital currency values.
Alvarez-Ramirez et al., (2018)	Long-range correlations and asymmetry in the bitcoin market.	Correlation in DFA and DCCA	Coin Market Cap	The findings might reveal insights into the persistence of certain patterns over extended periods and the presence of asymmetry in how Bitcoin prices fluctuate and respond to market conditions.
Anupriya and Garg (2018)	Autoregressive integrated moving average model based prediction of bitcoin close price.	ARIMA model	coindesk.com	The results of this investigation are expected to offer understanding into the efficiency and precision of the ARIMA pattern in predicting the concluding values of BTC.

Table 2.2 Overview of Research Published on BTC Price Prediction (Cont.)

Reference	title	Technique	Data source	findings
Ardia et al., (2019)	Regime changes in bitcoin GARCH volatility dynamics	MSGARCH model	Data stream	The findings could potentially reveal insights into how different market regimes, such as periods of high volatility and low volatility, affect the dynamics of BTC price volatility.
Bartolucci et al., (2020)	The butterfly “affect”: Impact of development practices on cryptocurrency prices.	Granger-causality method	Github, Coin Market Cap	The findings of such a study might reveal the interplay between development practices within the cryptocurrency ecosystem and the resultant effects on price movements.
Bhambhwani et al., (2019)	Do fundamentals drive cryptocurrency prices? Available at	Dynamic ordinary least squares method	Coinmetrics	The exact findings would be available in the document referred to in the passage, but it would likely present insights into the relationship between fundamental factors and cryptocurrency price movements.

Table 2.2 Overview of Research Published on BTC Price Prediction (Cont.)

Reference	title	Technique	Data source	findings
Bystrom and Krygier (2018)	What drives bitcoin volatility? Available at	Correlations, regressions, VAR, and impulse response	Luxembourg-based BTC exchange Bitstamp	The results could offer perspectives into the complexness of BTC instability and the variety of elements that can impact it.
Caporale and Zekokh (2019)	Modelling volatility of cryptocurrencies using Markov-switching GARCH models.	Markov-switching GARCH models	Coin Market Cap, CoinDesk price index	The results of this research are expected to offer understanding into the effectiveness of Markov-switching GARCH models in grasping the dynamic characteristics of cryptocurrency instability, possibly unveiling switching systems or trends in volatility behavior.
Charles and Darné (2019)	Volatility estimation for cryptocurrencies: Further evidence with jumps and structural breaks.	Four GARCH-type models	Coin Market Cap	The results offer proof of the existence of abrupt leaps or noteworthy structural alterations in digital currency instability.

Table 2.2 Overview of Research Published on BTC Price Prediction (Cont.)

Reference	title	Technique	Data source	findings
Charles and Darné (2019)	Volatility estimation for cryptocurrencies : Further evidence with jumps and structural breaks.	Four GARCH-type models	Coin Market Cap	The results could offer proof of the presence of leaps and structural interruptions in the dynamics of digital currency instability.
Dos Santos Maciel and Ballini (2019)	On the predictability of high and low prices: The case of bitcoin.	FCVAR model	coindesk.com	The findings may provide insights into the patterns, factors, and potential indicators that can be used to forecast the high and low prices of BTC.
Giudici and Abu-Hashish (2019)	What determines bitcoin exchange prices? A network VAR approach.	Correlation network and VAR model	cryptocoincharts.info	The findings would likely present insights into the interconnected relationships between various factors and how these elements collectively influence the pricing dynamics of BTC exchanges.

Table 2.2 Overview of Research Published on BTC Price Prediction (Cont.)

Reference	title	Technique	Data source	findings
Gunay (2019)	Impact of public information arrivals on cryptocurrency market: A case of Twitter posts on ripple.	Kapetanios unit-root test, Maki cointegration analysis and Markov regime switching regression analysis	Coin Market Cap	The findings would likely provide insights into the correlation between public information arrival, social media sentiment, and the resulting impact on Ripple's market behavior.
Guo and Antulov-Fantulin (2018)	Predicting short-term Bitcoin price fluctuations from buy and sell orders	Temporal mixture model	They are not mentioned	The suggested frameworks performed more effectively than alternative models in forecasting alterations in BTC's value.
Karalevicius et al., (2018)	Using sentiment analysis to predict interday bitcoin price movements	Natural language processing techniques, lexicon-based sentiment analyzer	Expert news media, CoinDesk, Coin telegraph, News BTC	The findings may provide insights into the relationship between public sentiment, social media discussions, and the short-term price dynamics of BTC
Kim et al., (2016)	Predicting fluctuations in cryptocurrency transactions based on user comments and replies.	MF-DCCA	Crypto-compare	The findings may offer insights into the potential correlation between user sentiment or interaction on social platforms and the corresponding impact on cryptocurrency transaction volumes or patterns.

Table 2.2 Overview of Research Published on BTC Price Prediction (Cont.)

Reference	title	Technique	Data source	findings
Roy et al., (2018)	Customer engagement behaviors: The role of service convenience, fairness and quality	ARIMA, AR, and MA models	CoinDesk	The findings of this research would likely delve into the impact of these factors on customer engagement, potentially providing insights into how businesses can enhance customer experiences and relationships through the strategic management of these elements.
Sovbetov (2018)	Factors influencing cryptocurrency prices: Evidence from bitcoin, ethereum, dash, litcoin, and monero	ADF unit-root test and bound testing approach	Bit Info Charts, Finance, World Bank, and Google Trends	The findings unveiled that market beta, transaction volume, and instability exert a significant influence on the values of all five digital currencies over both the immediate and extended term.
Stosic et al., (2018)	Collective behavior of cryptocurrency price changes	Random matrix theory and minimum spanning trees	Coin Market Cap	The findings could provide insights into the overall behavior of cryptocurrency markets, including potential collective trends, correlations, or systemic movements in the pricing of various cryptocurrencies.
Walther et al., (2019)	Exogenous drivers of bitcoin and cryptocurrency volatility—A mixed data sampling approach to forecasting	GARCH–MIDAS framework	Coin Market Cap, CRIX from thecrix.de	The findings may present insights into the impact of various exogenous variables, such as market trends, economic indicators, or geopolitical events, on cryptocurrency price volatility.

The chart 2.2 illustrates some pertinent research in recent years on the BTC price forecast issue. The distinction between the present investigation and earlier inquiries is thoroughness and all-inclusiveness. This research compares different types of prediction methods, including conventional statistical methods (ARIMA, GARCH), traditional method of regression (OLS), and emerging machine learning methods (ANN, NARX, ANFIS, and SVR). The contrastive examination in the ongoing study has not been carried out previously. Furthermore, a range of metrics, including macro-level metrics, micro-level metrics, blockchain data, and technical indicators have been used to examine the fundamental factors as predictors of BTC price.

Based on the current body of knowledge, a comprehensive examination involving nearly all classes of indicators has not been conducted. Furthermore, as indicated in prior sections, researchers continue to question whether macro-level indicators and blockchain metrics possess potential predictive power over the short or long term. This investigation aims to address this matter. Additionally, most of the research on BTC price projection involves practical analyses. Nonetheless, this present study initially explores the BTC price forecasting challenge from the standpoint of economic theories, encompassing demand and supply theory, microstructure theory, and cost-based pricing theory. Subsequently, it identifies the correlated variables influencing BTC prices. Subsequently, it verifies the predictive capability of the attributes through the utilization of both emerging machine learning models and conventional techniques.

literature review of GARCH models

In 2003, Engle received the "Nobel Prize in Economics." (jointly with C. Granger) for his contributions to analyzing time series techniques with time-varying volatility (ARCH) (Orskaug, 2009). The Danish economist T. P. Bollerslev introduced the extended ARCH model, referred to as GARCH, in 1986 subsequent to completing his doctorate under the guidance of Engle (Flores-Sosa et al., 2023). This framework is a more comprehensive version of the ARCH model and has been demonstrated to be superior in forecasting volatilities compared to the ARCH model. The most evident utilization of MGARCH (multivariate GARCH) frameworks is the examination of the connections between the fluctuations and co-fluctuations of multiple markets. (Chen et al., 2020; Marques, 2022; Shiferaw, 2019; Song et al., 2019). Multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models were initially developed in the late 1980s and the early 1990s.

Bollerslev et al. (1988) suggested the earliest multivariate GARCH framework for the conditional variance–covariance matrix, precisely the VEC model, which represented a notable stride in the initial direction. However, this framework is extremely comprehensive and exceedingly difficult to implement in real-world situations. The multitude of parameters in the framework is substantial in comparison to the framework's dimension, rendering it challenging to ensure the positive definiteness of the variance–covariance matrix in the model. Consequently, a section of the subsequent literature seeks to simplify this framework.

Bauwens et al. (2006) introduced a simplified version of the VEC model, the Diagonal–VEC model. This version substantially reduced the number of parameters, and it is relatively easier to establish the conditions to guarantee the positive definiteness of the variance–covariance matrix. However, as the variance or covariance in the model is solely based on its past observations, it is unable to capture the relationships between different variances and covariances.

R. F. Engle and Kroner (1995) Present the BEKK framework, which can be observed as a truncated version of the VEC mechanism. The BEKK framework has a beneficial attribute, that being the assurance of the non-negative definiteness of the conditional variance-covariance matrix through its own structure. Nevertheless, the quantity of variables in the BEKK framework escalates swiftly with the size of the framework. Besides, deciphering the significance of the framework's coefficients poses a difficulty. More streamlined frameworks include the Diagonal-BEKK framework and the Scalar-BEKK framework. The Diagonal-BEKK framework faces a similar problem to the Diagonal-VEC framework, though it significantly reduces the amount of variables. The Scalar-BEKK framework is excessively restrictive given that it enforces identical dynamics upon all variances and correlations.

Alexander (2001) proposed the Orthogonal-GARCH framework. The author utilized principal component analysis to uncover the hidden independent elements, which are assumed to possess unique individual GARCH configurations. The tally of variables can be diminished. However, a significant limitation of this technique is the complicated interpretation of the variables, akin to the BEKK framework. An alternative path for MGARCH frameworks is to obliquely model the interrelation among the series rather than explicitly modeling the variance-correlation matrix.

Bollerslev (1990) pioneered the introduction of a form of persistent conditional correlation (CCC) framework in which the conditional correlation matrix is assumed to be constant, and thus the conditional covariances are linked to the product of the respective conditional standard deviations. The establishment of the CCC framework is groundbreaking, as it involves significantly fewer variables, it reduces a substantial amount of computational workload since only a single correlation matrix needs to be inverted at each iteration using the maximum likelihood approach, and it inherently ensures the non-negative definiteness of the variance-correlation matrix. However, the assumption that the conditional correlation matrix is constant over time is impractical for numerous real-world scenarios.

Lien et al. (2002) developed the CCC framework to permit the conditional correlation matrix to fluctuate over time. A further hurdle for models with changing correlations is ensuring that the shifting conditional correlation matrix remains positively definite at every point. This investigation adds to the comprehension of the changing associations among stock market indices, which is vital for diversifying investments and managing risks.

R. Engle (2002) outlined the changing conditional correlation (DCC) framework defined a GARCH–style dynamic matrix process and then transformed the variance–covariance matrix into the correlation matrix. Engle's DCC framework has been widely applied in various domains of finance, including portfolio optimization, risk management, and volatility forecasting. Its flexibility in capturing changing correlations makes it particularly valuable for examining the relationship between financial assets, such as digital currencies like BTC, and other financial instruments.

Cappiello et al. (2006) advocated for the asymmetric comprehensive dynamic conditional correlation (AG–DCC) framework. The AG–DCC approach permits personalized news impact and smoothing parameters and accounts for conditional imbalances in correlation dynamics. It provides valuable insights into capturing the asymmetric behavior of conditional correlations in financial markets.

(Vargas, 2006) proposed the asymmetrical block dynamic conditional correlation (ABDCC) framework. This model extends the traditional dynamic conditional correlation (DCC) model by incorporating asymmetric effects in both the conditional volatilities and the conditional correlations of multivariate time series data. The ABDCC model allows for different levels of correlation changes during market upswings and downturns, capturing the divergences observed in financial data.

Literature review of machine learning in financial field

With the swift advancement of information technology in the recent years, the continuous improvement of computer processing ability and the gradual digitalization of the way of obtaining financial market transaction information, it is no longer an imaginary topic to obtain a large amount of financial market data at a high speed while using computers to conduct high-frequency transactions that only take a few milliseconds. Compared with high-frequency trading, it is difficult for traditional trading methods to obtain stable and timely trading signals from financial markets with messy information, so it is difficult to obtain competitive advantages in the market. Building on this, numerous researchers attempt to employ machine learning algorithms in the realm of financial investment.

Kearns and Nevmyvaka (2013) selected three machine learning approaches and applied them in high-frequency trading within financial markets. Drawing from the results of their repeated experiments, they dismissed the notion that high-frequency trading models utilizing machine learning are perceived as "black boxes" and underscored the importance of accurate representation of data features and parameter optimization on model training outcomes. It is not uncommon to apply support vector machine algorithm or its derivative improved algorithm to the research of financial investment.

Y. Chen and Hao (2020) merged PLR and WSVM to construct a PLR-WSVM framework for forecasting upcoming stock trading signals, and chose 20 stocks listed in Shanghai Stock Exchange for overlapping training and testing. The robustness of the framework and the accuracy of stock market prediction are verified.

Ari and Alagoz (2023) evaluated three distinct machine learning categorization algorithms based on the needs of maximizing investment profits and minimizing investor uncertainties. The findings reveal that the model combining support vector machine and particle swarm optimization algorithm attains the highest precision and resilience in projecting historical stock data.

Aloud (2020) attempted to investigate the impact of diverse attribute selection, training methodologies, and training set size on the predictive outcome of conventional machine learning approaches such as support vector machine on foreign currency exchange rates. Additionally, alternative machine learning approaches apart from support vector machine have also attracted significant attention among researchers.

Thakkar & Lohiya (2021) evaluated the effectiveness of stock price forecast models such as random forest, support vector machine, and naive Bayes with varied data as input. Tests demonstrate that for the Indian stock market, the efficiency of random forest algorithm with ten technical indicators as input data is noticeably superior to other models.

Yang and Gao (2021) combined the random forest algorithm with the GARP model to try to solve the problem of high-quality stock selection. Furthermore, the stock choices obtained from the model demonstrated notable efficacy in the simulated trading sessions of China's stock market.

Jeong et al. (2018) creatively integrated semi-supervised machine learning with investor sentiment analysis, extracted sentiment indicators from the firm's financial data and online public sentiment, and employed graph-based semi-supervised learning to evaluate corporate credit risk and identify risk signals. Ultimately, stock trading choices were derived from the risk signals, which underwent historical testing on the U.S. stock market and yielded substantial gains.

Phuensane and Boonpong (2022) merged the neural network framework with the three factor structure and utilized it in the primary board market in mainland China. Upon comparison, it was determined that the neural network framework outperformed other frameworks in forecasting stock prices in the primary board market. Some researchers also integrated GFS algorithm to enhance the stock price forecast using ANN artificial neural network. The empirical findings showed that the efficiency of the improved framework surpasses the research methods utilized by other scholars.

Ticknor (2013) incorporated Bayesian theorem into artificial neural network framework to anticipate and assess stock prices with the aim of lessening model over fitting and enhancing model generalization capability.

Zhang et al. (2019) utilized the artificial neural network (ANN) to foresee the daily trading volume rate of NASDAQ. This investigation aimed to explore the possibility of employing neural network frameworks for predicting the turnover rate, a pivotal gauge of market liquidity. By gathering historical data on turnover rates and pertinent market factors, the scholars educated an ANN framework to grasp the non-linear correlations and configurations inherent in the data. The educated framework was consequently utilized to project outcomes on unobserved data, enabling the estimation of potential turnover rates.

Sezer and Ozbayoglu (2019) used the ANN to select technical indicators and select the optimal technical indicators on the premise of meeting the purchase conditions and holding strategies. The use of ANN for selecting technical indicators is a common application in finance and trading. ANN models can be trained to analyze historical data and identify the most relevant technical indicators that are likely to have predictive power for forecasting market trends or making trading decisions.

2.3.5 Literature review of Asymmetric cointegration and causality

Supposing there exists a cointegration association, notably an uneven cointegration association, amid BTC and conventional financial resources, such as Gold, raw petroleum, and the U.S. currency. Based on the cointegration analysis, the cause-and-effect connection between BTC and traditional financial assets, particularly the uneven cause-and-effect connection, is additionally established. Whether the cause-and-effect connection shifted before and after the Covid-19 outbreak is also one of the research objectives.

BTC and Gold

BTC, as a developing asset with certain resemblances to Gold, is frequently denoted as "digital Gold" or "Gold 2.0". (Baur & Hoang, 2021; Jareño et al., 2020). Therefore, many researchers have concentrated specifically on the connection and disparities between BTC and Gold. Dyhrberg (2016b) discovered that BTC and Gold demonstrate analogous hedging characteristics. Certain scholars argue that there exists a robust correlation between BTC and Gold (Bouoiyour et al., 2019; Shahzad et al., 2019). Likewise, Shahzad et al. (2019) also acknowledged BTC and precious metal as a secure refuge for wealth. particularly during periods of economic uncertainty. However, there are divergent viewpoints as well. For example, Long et al. (2021) determined that BTC lacks the equivalent hedging characteristics as Gold. The connection between BTC and Gold is feeble (Kang et al., 2019; Wu et al., 2019). Al-Khazali et al. (2018) asserted that BTC and Gold are autonomous. Additionally, academics have also concentrated on the transmission impact between BTC and Gold. (Yu et al.,2021; Zha et al., 2023), fluctuating linear associations (Jin et al., 2019; Kang et al., 2019; Klein et al., 2018), and non-linear linkages (Jareño et al., 2020; Kumar et al., 2023; Zwick & Syed, 2019).

BTC and Crude Oil

There exists an innate affirmative connection between BTC and petroleum because BTC mining necessitates the utilization of crude oil (Das et al., 2020). Depreciation of fiat currencies due to inflationary increases in crude oil prices. Fiat currencies have seen varying degrees of depreciation, a phenomenon that suggests increased demand for BTC from investors, leading to a rise in BTC prices (Kilian, 2009). In light of this, researchers have been focused on the investigation of the correlation between BTC and petroleum. Certain scholars, like (Li et al., 2022; Su & Li, 2020; Zha et al., 2023), examines the factors influencing the transfer of risk against BTC, oil and other financial assets and the pathways in the transmission process. Several researchers have found and confirmed a strong correlation and instability between BTC and oil (Attarzadeh & Balcilar, 2022; Ozturk, 2020b).

BTC and the US dollar

In addition to gold and oil, which are financial assets, BTC investors are focusing more on investing in US dollars. Many experts are turning their attention to studying the correlation between BTC, gold, oil and the US dollar. For example, G. Cao and Ling (2022) illustrated the application of asymmetric dependency structures between BTC, US currency and Gold. Das et al. (2020) assessed the hedging and safe haven attributes of BTC against petroleum, and compared it with Gold and the U.S. currency. Dyhrberg (2016b) described the volatility between BTC, gold and the US dollar , highlighting their role in portfolio and risk management. Bhuiyan et al. (2021) uncovered the precedence-trail correlation among BTC, petroleum, Gold, and the U.S. currency, construing it as a causative link. There are also research endeavors that exclusively concentrate on the association between BTC and the U.S. currency. For instance, Szetela et al. (2016) evaluated the correlation between BTC and various monetary units, encompassing the American currency. Antoniadis et al. (2018) examined the impact of BTC on the USDX, highlighting the asymmetrical link between BTC and the US dollar. Mokni and Ajmi, (2021) contrasted the utmost Granger causality between virtual currencies and the U.S. currency pre and post the global health crisis. The scrutiny of BTC and conventional financial assets is comprehensive, establishing a robust foundation for this analysis. Nonetheless, numerous studies have contradictory discoveries, and the transformation in the association between BTC, around the time of the COVID-19 pandemic, many researchers were actively exploring the relationship between traditional financial assets There has been more attention from experts on the riskiness and hedging characteristics of BTC and the impact of asymmetric risk transfer. From the current research, it is found that there is little research on the correlation between BTC and traditional financial assets (Almeida & Gonçalves, 2022; Murty et al, 2022; Shahzad et al., 2019; Wang et al., 2019). Only a restricted group of academics have delved into the causation between BTC and the U.S. currency or petroleum, without thoroughly establishing the asymmetric causation between BTC and traditional fiscal assets. Consequently, research on asymmetric covariance and asymmetric causality between BTC and traditional financial assets (especially gold, oil, and the U.S. dollar) is much needed. The importance of this study is predominantly illustrated in the subsequent domains: First, the uneven co-integration relationship between BTC and conventional financial assets was explored by comparing the viewpoints on co-integration linkage. (Tadi & Kortchemski, 2021; Tiffani et al., 2023). It is demonstrated that asymmetrical co-integration connections can unveil more economic phenomena: there is an absence of co-integration relationship between BTC and conventional financial assets, but a significant asymmetrical co-integration association exists. Subsequently, the asymmetric influence between BTC and conventional financial assets was scrutinized. It is disclosed that there is Granger causation between petroleum and BTC, and between the adverse impact of petroleum and BTC price downturn. Third, further comparison was conducted on the asymmetrical Granger causation between BTC and traditional financial assets pre and post the COVID-19 outbreak while relying on the application of. (Mokni & Ajmi, 2021). The results indicate that the decline in Gold values due to the pandemic does not serve as a Granger cause for the rise in BTC values, while the drop in petroleum prices emerges as a Granger cause for the decline in BTC values.

2.3.6 A Bibliometric and Visual Examination in the Area of BTC

An all-encompassing collection of data and assessment of a specific subject is advantageous in aiding scholars to gain deeper insight into the fundamentals and prospective progress of a field. (Adams & McGuire, 2022). At present, bibliometric evaluation is one of the more favored approaches for scrutinizing vast quantities of scholarly works. A substantial volume of bibliometric information can be accessed through scientific resources such as figures, and repositories such as Scopus and Web of Science, as well as an array of bibliometric utilities, aid in scrutinizing them in a logical manner. In this investigation, the Scopus repository was utilized, which is acknowledged as the largest scholarly database of academic importance. This examination assessed studies that incorporated "BTC" and "Gold or Oil or Dollar" in the abstract/keywords or title. Bibliometric investigations succinctly describe the communal and structural associations between varied research constituents (e.g. authors, nations, institutions, and subjects). Techniques for bibliometric assessment encompass evaluation of efficiency and scientific depiction. Evaluation of efficiency employs citation and publication-linked benchmarks. Evaluation of efficiency examines the contributions of research constituents to a particular field. (Donthu et al., 2021; Post et al., 2020). Scientific mapping techniques incorporate citation assessment, co-citation assessment, bibliographic coupling, co-word evaluation, and co-authorship evaluation (Bernatović et al., 2022; Gan et al., 2022; González-Valiente et al., 2021). The period was defined from 2012 to 2023. The investigation was carried out in November 2023, and the subsequent standards were employed for preservation. Retention standards were as follows: (1) Categorization in correspondence with Scopus. (2) The paper's language was English. A combined total of 857 documents were acquired, and Figure 2.8 demonstrates the choice approach.

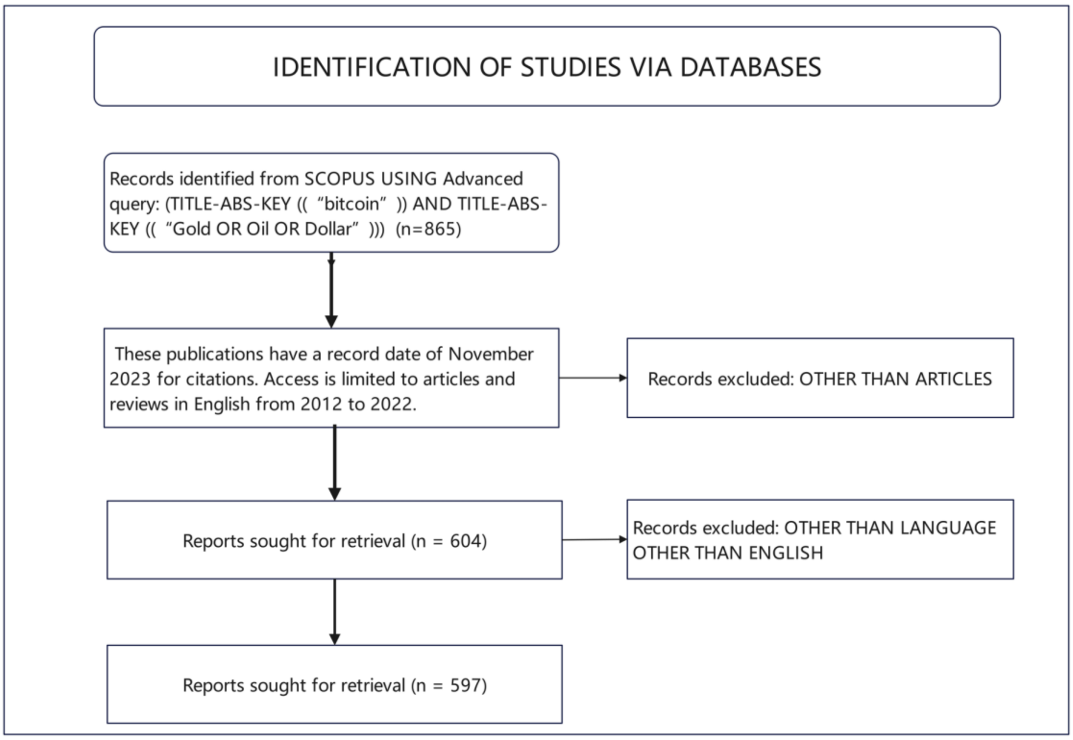

Figure 2.8 Illustrates the selection strategy

Examining publications. The aim of employing econometrics to scrutinize temporal attributes is to investigate variations and patterns in the research subject at various time intervals. A substantial quantity of articles has been published on BTC and Gold, Oil, and the US currency over the 2012-2023 timeframe. Figure 2.9 illustrates the volume of papers published annually and observes a notable increase in the number of publications, especially in the last four years. These findings indicate that the examination of BTC is attracting growing interest from researchers.

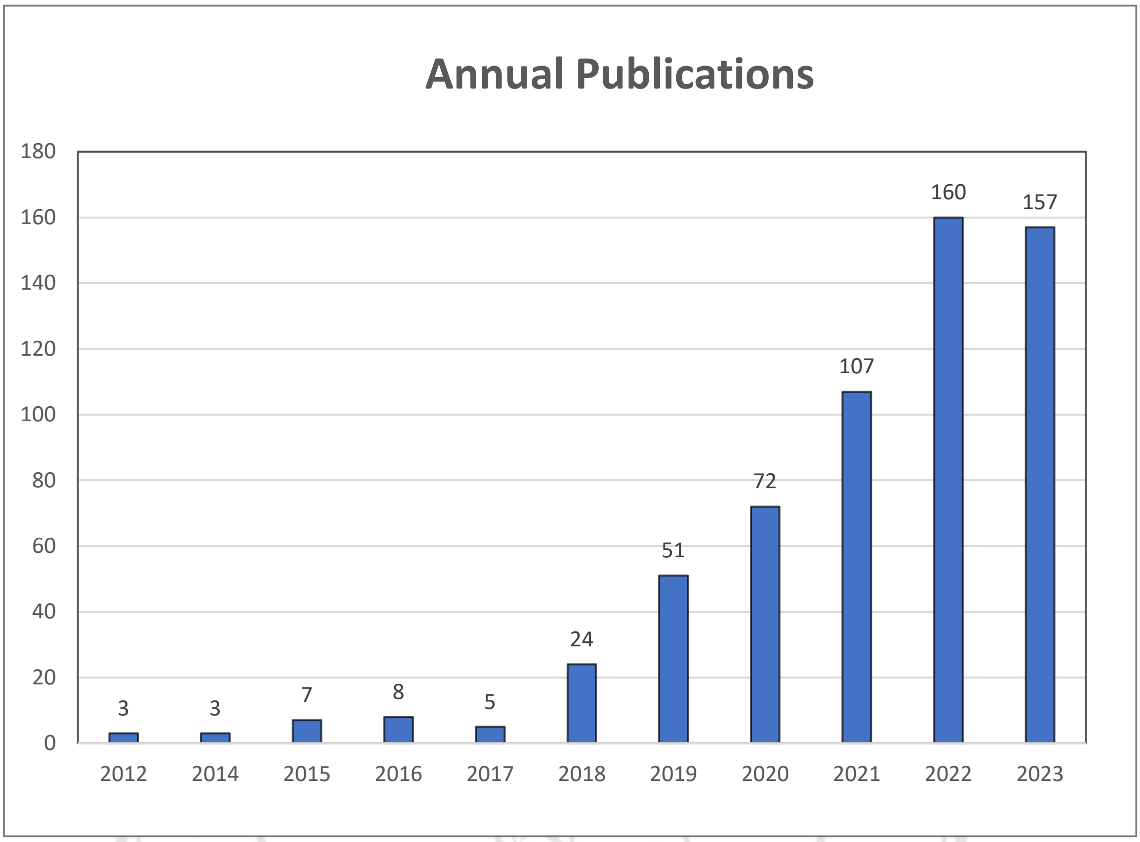

Figure 2.9 BTC papers published annually **(**2012–2022**)**

Analysing the citation structure identifies the main authors and articles that have contributed to the study of the correlation between BTC and Gold Petrodollar. Table 2.3 lists the 30 highly cited papers from 2012 to 2023. The most cited papers are those by Tschorsch F.; Scheuermann B. et al. who develop and organise the results and directions of research on various aspects of BTC. The second most cited paper is by Dyhrberg A.H., that examines the financial asset capabilities of BTC using a GARCH model. The works of (Bouri et al., 2017) apply time-varying conditional correlation modeling to examine whether BTC can serve as a financial instrument for the principal stock benchmarks worldwide, bond holdings, petroleum, precious metal, broad commodity benchmarks, and the U.S. currency benchmark. The security and privacy aspects of BTC will be systematically studied by (Bouri et al., 2017) use the uneven GARCH approach employed in the analysis of Gold to investigate the risk management capabilities of BTC.

Table 2.3 The 30 most cited papers about BTC during 2012–2023

R	**Authors**	**Title**	**Year**	**Cited by**
1	Tschorsch F.; Scheuermann B.	Bitcoin and beyond: A technical survey on decentralized digital currencies	2016	1129
2	Dyhrberg A.H.	Bitcoin, Gold and the dollar - A GARCH volatility analysis	2016	841
3	Bouri E.; Molnár P.; Azzi G.; Roubaud D.; Hagfors L.I.	On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?	2017	708
4	Conti M.; Sandeep K.E.; Lal C.; Ruj S.	A survey on security and privacy issues of bitcoin	2018	569
5	Dyhrberg A.H.	Hedging capabilities of bitcoin. Is it the virtual Gold?	2016	530
6	Corbet S.; Larkin C.; Lucey B.	The contagion effects of the COVID-19 pandemic: Evidence from Gold and cryptocurrencies	2020	497
7	Klein T.; Pham Thu H.; Walther T.	Bitcoin is not the New Gold – A comparison of volatility, correlation, and portfolio performance	2018	433
8	Dwyer G.P.	The economics of Bitcoin and similar private digital currencies	2015	425
9	Ali M.; Alam N.; Rizvi S.A.R.	Coronavirus (COVID-19) — An epidemic or pandemic for financial markets	2020	406
10	Shahzad S.J.H.; Bouri E.; Roubaud D.; Kristoufek L.; Lucey B.	Is Bitcoin a better safe-haven investment than Gold and commodities?	2019	351
11	Guesmi K.; Saadi S.; Abid I.; Ftiti Z.	Portfolio diversification with virtual currency: Evidence from bitcoin	2019	337

Table 2.3 The 30 most cited papers about BTC during 2012–2023 (Cont.)

R	**Authors**	**Title**	**Year**	**Cited by**
12	Ji Q.; Bouri E.; Lau C.K.M.; Roubaud D.	Dynamic connectedness and integration in cryptocurrency markets	2019	309
13	Conlon T.; Corbet S.; McGee R.J.	Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic	2020	306
14	Selmi R.; Mensi W.; Hammoudeh S.; Bouoiyour J.	Is Bitcoin a hedge, a safe haven or a diversifier for Oil price movements? A comparison with Gold	2018	289
15	Baur D.G.; Dimpfl T.; Kuck K.	Bitcoin, Gold and the US dollar – A replication and extension	2018	282
16	Hussain Shahzad S.J.; Bouri E.; Roubaud D.; Kristoufek L.	Safe haven, hedge and diversification for G7 stock markets: Gold versus bitcoin	2020	255
17	Bouri E.; Shahzad S.J.H.; Roubaud D.; Kristoufek L.; Lucey B.	Bitcoin, Gold, and commodities as safe havens for stocks: New insight through wavelet analysis	2020	214
18	Smales L.A.	Bitcoin as a safe haven: Is it even worth considering?	2019	183
19	Al-Yahyaee K.H.; Mensi W.; Yoon S.-M.	Efficiency, multifractality, and the long-memory property of the Bitcoin market: A comparative analysis with stock, currency, and Gold markets	2018	173
20	Krause M.J.; Tolaymat T.	Quantification of energy and carbon costs for mining cryptocurrencies	2018	173
21	Chen Z.; Li C.; Sun W.	Bitcoin price prediction using machine learning: An approach to sample dimension engineering	2020	170

Table 2.3 The 30 most cited papers about BTC during 2012–2023 (Cont.)

R	**Authors**	**Title**	**Year**	**Cited by**
22	Mariana C.D.; Ekaputra I.A.; Husodo Z.A.	Are Bitcoin and Ethereum safe-havens for stocks during the COVID-19 pandemic?	2021	168
23	Dutta A.; Das D.; Jana R.K.; Vo X.V.	COVID-19 and Oil market crash: Revisiting the safe haven property of Gold and Bitcoin	2020	165
24	Borri N.	Conditional tail-risk in cryptocurrency markets	2019	164
25	Le T.N.-L.; Abakah E.J.A.; Tiwari A.K.	Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution	2021	161
26	Su C.-W.; Qin M.; Tao R.; Umar M.	Financial implications of fourth industrial revolution: Can bitcoin improve prospects of energy investment?	2020	155
27	Griffin J.M.; Shams A.	Is Bitcoin Really Untethered?	2020	150
28	Wu S.; Tong M.; Yang Z.; Derbali A.	Does Gold or Bitcoin hedge economic policy uncertainty?	2019	146
29	Sensoy A.	The inefficiency of Bitcoin revisited: A high-frequency analysis with alternative currencies	2019	145
30	Huynh T.L.D.; Hille E.; Nasir M.A.	Diversification in the age of the 4th industrial revolution: The role of artificial intelligence, green bonds and cryptocurrencies	2020	136

Keyword analysis. By tallying the frequency of simultaneous occurrences of keywords, it is possible to reveal the connections between keywords and the relationship between topics, which in turn helps to reveal the hotspots and structure of the research field. In our study, we selected author keywords as the statistical object of keyword analysis. Among all 2293 author keywords, we set the keywords with at least 9 occurrences as the object of analysis, and as a result, only 61 author keywords reached the critical value. The co-occurrence network of the main author keyword clusters drawn using the VOS browser software is shown in Figure 2.10. The table indicates that based on the primary author keywords, the principal subject matters can be categorized into six domains: the hazard of BTC (red grouping), the association between BTC and conventional financial assets (green grouping), the instability of BTC and traditional financial assets (blue grouping), the transaction of BTC (yellow grouping), and the prognosis of BTC investment (purple grouping), and the fluctuating correlation of BTC (light blue grouping).

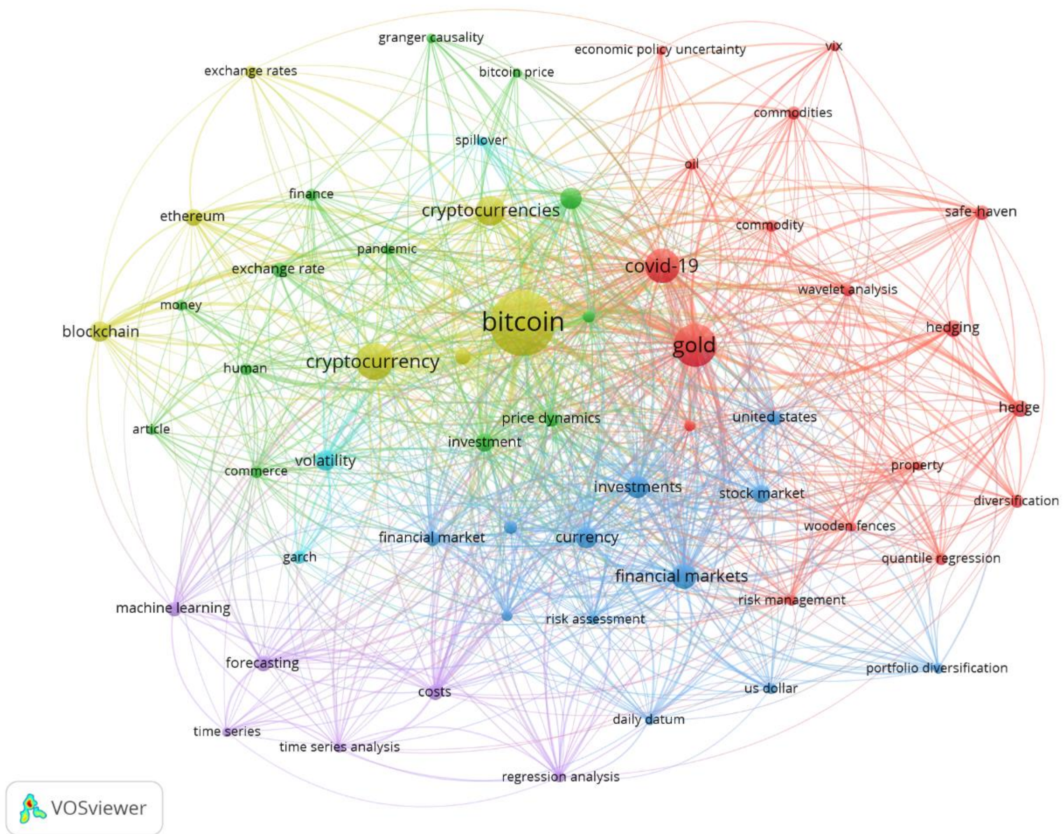

Figure 2.10 Co-occurrence network of major author keywords

2.4 Summary

This chapter provides relevant research on the BTC prediction problem. It begins with a discussion of cryptocurrencies, particularly BTC and its underlying technology, the blockchain. Afterwards, relevant works on cryptocurrencies in the existing literature are presented. In particular, the debate among authors about the short- or long-term predictive power of macroeconomic and blockchain information properties is discussed. In addition, researchers' doubts about the ability of machine learning to beat traditional models are discussed. The relationship between BTC and traditional finance includes dynamic correlations, and static correlations. Finally, some differences between the existing literature and current research are identified.

It also discusses the significance of cryptocurrency prediction in economics, the importance of machine learning methods in the price forecasting matter, and examines BTC price forecast from the viewpoint of economic principle.

Through the above literature review, we can find that a lot of work has been done by previous authors on portfolio and machine learning. These have laid a good foundation for this study. However, we can also find that most econometric models, such as DCC-GARCH, multivariate GARCH, and stochastic volatility models, have been used to study portfolios since correlation and volatility are important information in portfolio analysis, while machine learning abandons the efficient market hypothesis and related theories in economics to make investment decisions only from the perspective of data forecasting. Moreover, there are few methods that combine machine learning and econometric models for price prediction, but not yet for portfolio allocation. Moreover, ANN and KNN have been the main methods for stock price prediction. In view of this, we will combine machine learning methods with DCC-GARCH models to provide more data information for ANN and KNN, which is a particularly interesting research topic.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The objective of this dissertation is to examine the influence of the connection between BTC and conventional financial instruments like valuable metal Gold, unrefined oil Petroleum, and the currency of the United States, the dollar. The thesis examines the established connection between BTC and conventional financial instruments through the disparate cointegration analysis and the asymmetric Granger Causality analysis. A DCC-GARCH model is used to analyse the changing correlation between BTC and traditional financial assets (oil, BTC and the precious metal gold) through the particular period of the COVID-19 outbreak. The goal is to enhance investment decision-making for BTC. A DCC-GARCH framework using a neural network approach is suggested and applied to BTC's historical data, assessing its correlation and risk spillover with traditional financial assets. The thesis adopts a quantitative approach to address the research queries. Focusing on each methodology, a thorough summary and overview are provided, which are recapitulated in the conclusion of the segment.

3.2 Methodology

3.2.1 Unit Root Test

The concept of the unit root test was first introduced by economist Denis Sargan and Alok Bhargava in the 1970s (Hendry, 2003). They formulated this examination as a method to determine the existence of a foundational root in time series data, suggestive of non-stationarity in the information. The unit root test has several classifications, including:

1. Expanded Dickey-Fuller (ADF) Examination: This examination is a continuation of the Dickey-Fuller examination and is frequently utilized to examine the existence of a basic root in a dataset of time series.It allows for more complicated time series structures and provides more reliable results.

2. Phillips-Perron (PP) Test: This examination is another well-known basic root examination that is akin to the ADF test but possesses specific distinctions in its execution and statistical characteristics.

3. Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Examination: In contrast to the ADF and PP examinations, the KPSS test is employed to examine consistency rather than the existence of a simple root. It supplements the ADF and PP tests and is frequently utilized in combination with them to offer a more thorough analysis of time series information.

These are the three primary classifications of the unit root test, each with its own specific strengths and applications in time series analysis.

3.2.1.1 Augmented Dickey-Fuller Test (ADF)

The Augmented Dickey-Fuller (ADF) examination was presented by the economists David Dickey and Wayne Fuller in 1979 (Pantula et al., 1994). The examination was created to scrutinize time sequence information and detect the existence of a basic root, which signifies lack of stationarity in the information. The ADF examination is extensively utilized in econometrics and diverse areas of study for examining and formulating models for time sequence information.

The Augmented Dickey-Fuller (ADF) examination is a statistical examination employed to ascertain whether a basic root exists in a time sequence dataset. A basic root indicates that the information is not stationary, signifying that its statistical characteristics such as average and fluctuation are not consistent over time.

The zero hypothesis of the ADF examination is that a basic root is present, indicating non-stationarity. The opposing hypothesis is that the information is consistent. The test involves estimating a regression model of the form:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \ldots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \quad (3.1)$$

Where:

- $y_{(t)}$ represents the time series data

- $\Delta y_{(t)}$ denotes the differenced series

- α, β, and γ are parameters to be estimated

- $\varepsilon_{(t)}$ is the error term

- p is the lag order

The ADF test then evaluates the significance of the coefficient γ, indicating that the presence of a basic root in the data has been detected. If γ is determined to be statistically significantly distinct from zero, the null hypothesis of a unit root is dismissed, signifying that the data is consistent.

3.2.1.2 Phillips-Perron (PP) Test

The Phillips-Perron (PP) examination was put forward by economists Peter C.B. Phillips and Pierre Perron in 1988. This examination is an extension of the basic root examination and is frequently employed to examine the consistency of time series information. The Phillips-Perron (PP) initial root examination diverges from the ADF test mainly in its handling of serial correlation and heteroskedasticity in the errors. In particular, while the ADF test utilizes parametric autoregression to estimate the ARMA structure of the errors in the test regression, the PP test overlooks any serial correlation in the test regression. The test regression for the PP test is

$$\Delta y_t = \boldsymbol{\beta}' \mathbf{D}_t + \pi y_{t-1} + u_t \quad (3.2)$$

where u_t is $I(0)$ and may be heteroskedastic. The PP test corrects for any serial correlation and heteroskedasticity in the test regression error u_t by directly modifying the test sta t_π=0 and $T\hat{\pi}$.These modified statistics are denoted as Z_t and Z_π and are given in the following equation

$$Z_t \quad = \left(\frac{\hat{\sigma}^2}{\hat{\lambda}^2}\right)^{\frac{1}{2}} \cdot t_{\pi=0} - \frac{1}{2}\left(\frac{\hat{\lambda}^2-\hat{\sigma}^2}{\hat{\lambda}^2}\right) \cdot \left(\frac{T \cdot SE(\hat{\pi})}{\hat{\sigma}^2}\right) \tag{3.3}$$

$$Z_\pi = T\hat{\pi} - \frac{1}{2}\frac{T^2 \cdot SE(\hat{\pi})}{\hat{\sigma}^2}\left(\hat{\lambda}^2 - \hat{\sigma}^2\right) \tag{3.4}$$

The terms $\hat{\sigma}^2$ and $\hat{\lambda}^2$ are consistent estimates of the variance parameter

$$\sigma^2 = \lim_{T\to\infty} T^{-1} \sum_{t=1}^{T} E\left[u_t^2\right] \tag{3.5}$$

$$\lambda^2 = \lim_{T\to\infty} \sum_{t=1}^{T} E\left[T^{-1} S_T^2\right] \tag{3.6}$$

Where $S_T = \sum_{t=1}^{T} u_t$. The sample variance of the least squares residual $\hat{u}_t$is a consistent estimate of σ^2 and the Newey-West long-run variance estimate of u_t using $\hat{u}_t$ is a consistent estimate of λ^2 . Under the null hypothesis of $\pi = 0$, the PP $t_{Z}$and $Z_\pi$statistics have the same asymptotic distributions as the ADF t-statistic and the normalised deviation statistic. One of the benefits of the PP examination compared to the ADF examination is that the PP test is resilient to a broad form of heteroscedasticity in the error term u_t. Another advantage is that the user is not required to designate a lag length for the examination regression.

The paper deploys ADF and PP approaches to examine the evenness of the residuals, and if the outcome of the examination is steady, it suggests the presence of a cointegration association between BTC and global financial assets.

3.2.2 Asymmetric co-integration approach

Since Granger and Yoon (2002) suggested a notion of converting information into both aggregated favorable and unfavorable adjustments, the majority of researchers contributed to the exploration of lopsided cointegration, such as (Hatemi-J, 2020; Lardic & Mignon, 2008) etc. Following (Lardic & Mignon, 2008), the cumulative positive and negative changes of BTC can be expressed as follows:

$$Bitcoin_t^+ = \sum_{i=0}^{t-1} 1\{\Delta Bitcoin_{t-i} \geq 0\}\Delta Bitcoin_{t-i} \tag{3.7}$$

$$Bitcoin_t^- = \sum_{i=0}^{t-1} 1\{\Delta Bitcoin_{t-i} < 0\}\Delta Bitcoin_{t-i} \tag{3.8}$$

where I{} represents an indicator function, and $\Delta Bitcoin_{t-i}$ stands for the first difference of BTC at time t-i. Obviously, $\Delta Bitcoin_t = Bitcoin_t^+ + Bitcoin_t^-$. Similarly, we express the cumulative positive (negative) changes of Gold, crude Oil, and US dollar as $Gold_t^+(Gold_t^-)$, $Oil_t^+(Oil_t^-)$, and $USD_t^+(USD_t^-)$, respectively. Taking BTC and Gold as an example, suppose that a linear combination Y_t is constructed by

$$Y_t = \alpha_1 Bitcoin_t^+ + \alpha_2 Bitcoin_t^- + \alpha_3 Gold_t^+ + \alpha_4 Gold_t^- \tag{3.9}$$

If there exists a vector $\alpha' = (\alpha_1, \alpha_2, \alpha_3, \alpha_4\ )$ with $\alpha_1 \neq \alpha_2$ or $\alpha_3 \neq \alpha_4$ (and α_1 or $\alpha_2 \neq 0$ and α_3 or $\alpha_4 \neq 0$) such that Y_t is a stationary process, and then $Bitcoin_t$ and $Gold_t$ are asymmetrically - or directionally cointegrated. T The concept is that the correlation between the variables could differ when they rise or fall. To streamline and without sacrificing comprehensiveness, assume that only one element of each sequence is evident in the cointegrating association (3.8).

$$Y_{1t} = Bitcoin_t^+ - \beta^+ Gold_t^+ \text{ or } Y_{2t} = Bitcoin_t^- - \beta^- Gold_t^- \tag{3.10}$$

$$Y_{3t} = Bitcoin_t^+ - \beta^- Gold_t^- \text{ or } Y_{4t} = Bitcoin_t^- - \beta^- Gold_t^+ \tag{3.11}$$

Due to the nonlinear properties of $Y_{jt}, j = 1\ ,2,\ 3,\ 4$ OLS on Eq. (3.9) are likely to be biased in finite sample. For this reason, (Schorderet, 2003)suggests to estimate by OLS the auxiliary models:

$$\varepsilon_{1t} = Bitcoin_t^- + \Delta Bitcoin_t^+ - \beta^- Gold_t^- \text{ or } \varepsilon_{2t} = Bitcoin_t^+ + \Delta Bitcoin_{1t}^- - \beta^+ Gold_t^+ \tag{3.12}$$

$$\varepsilon_{3t} = Bitcoin_t^+ + \Delta Bitcoin_t^- - \beta^- Gold_t^- \text{ or } \varepsilon_{4t} = Bitcoin_t^- + \Delta Bitcoin_{1t}^+ - \beta^+ Gold_t^+ \tag{3.13}$$

As demonstrated by (West, 1988), given that the explanatory variable has a linear time trend in average, the OLS approximation of Eqs. (3.12) or (3.13) is asymptotically normal, and regular statistical analysis can be conducted. To examine the zero hypothesis of no cointegration in contrast to the alternative of asymmetrical cointegration, the standard Engle and Granger approach can be used on Eqs. (3.12) and (3.13).

3.2.3 Asymmetric causality test

Hatei-j (2012) initially developed the unequal causality examination using the structure of a VAR(p) model. To assist comprehension, we establish a VAR(2) model to conduct an unequal causality examination. Once more, with the exception of BTC and gld, the VAR(2) models for pair ($Bitcoin_t^+$, $Gold_t^+$) can be expressed as follows:

$$Bitcoin_t^+ = \beta_{10} + \beta_{11}Bitcoin_{t-1}^+ + \beta_{12}Gold_{t-1}^+ + \gamma_{11}Bitcoin_{t-2}^+ + \gamma_{12}Gold_{t-2}^+ + u_{1t} \tag{3.14}$$

$$Gold_t^+ = \beta_{20} + \beta_{21}Bitcoin_{t-1}^+ + \beta_{22}Gold_{t-1}^+ + \gamma_{21}Bitcoin_{t-2}^+ + \gamma_{22}Gold_{t-2}^+ + u_{2t} \tag{3.15}$$

where β_{ij} and γ_{ij} represent parameters of lag variables, and u_{it}, i=1, 2 is error term. Similarly, VAR models for the pairs ($Bitcoin_t^-, Gold_t^-$), ($Bitcoin_t^+$, $Gold_t^-$), and ($Bitcoin_t^-$, $Gold_t^+$) also can be constructed. The null hypothesis is H0: $\beta_{12} = \gamma_{12} = 0$, and the alternative hypothesis is H1: $\beta_{12} \neq 0 \ or \ \gamma_{12} \neq 0 \ or \ both \neq 0$. Once we reject the null hypothesis, which implies positive Gold shock does Granger cause positive BTC shock. An F test or Wald test usually is used to test the null hypothesis. To determine the number of lag order p, we employed Hatemi-J criterion (HJC) to select the optimal lag order. Following (Hatemi-J, 2020), the HJC is expressed as

$$\text{HJC} = \ln\left(\left|\widehat{\Omega}_j\right|\right) + j\left(\frac{n^2 lnT + 2n^2 \ln(lnT)}{2T}\right),\ j = 0,1,\dots,p \tag{3.16}$$

where j is the lag order, n is the number of variables and T is the number of observations. $|\widehat{\Omega}_j|$ is the determinant of the variance-covariance matrix of error term in the VAR model based on the lag order p. The lower HJC, the superior model. Typically, financial data does not follow a normal distribution, and there is the presence of autoregressive conditional heteroskedasticity (ARCH) effects (Liu et al., 2020). To overcome this issue, the bootstrap Wald test is used in this study (see details in (Hatemi-J et al., 2017)).

3.2.4 Autoregressive moving average (ARMA)-GJR-GARCH models

Autoregressive moving average (ARMA)-GJR-GARCH frameworks are applied for the extended-term yield since the indices utilized in this document exhibit varying risk clustering over time. Presented by (Glosten et al., 1993), due to enabling leverage impacts, the ARMA-GJR-GARCH model has been broadly embraced for the purpose of refining time series information. Regarding leverage impact, it appears to be more crucial during periods of crisis. To be specific, the ARMA (r, m) process is characterized as:

$$y_t = c + \sum_{k=1}^{r} \varphi_k \, y_{t-k} + \sum_{k=1}^{m} \rho_k \, \varepsilon_{t-k} + b\sigma_t + \varepsilon_t \qquad (3.17)$$

where y_t means the conditional mean and ε_t represents the error term. The GJR-GARCH (p, q) model can be defined as below:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} (\alpha_i + \gamma_i I_{t-i}) \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad (3.18)$$

where:

$$I_{t-1} = \begin{cases} 0 & if \, \varepsilon_{t-1} \geq 0, \\ 1 & if \, \varepsilon_{t-1} < 0 \end{cases}$$

In addition, γ represent the leverage effect and ζ_t represents the i.i.d standard innovation variables. As a result, the error term can be computed by $\varepsilon_t = \sigma_t \zeta_t$, and ζ_t is assumed to be student-t distribution.

The proposed dynamic correlation structure is:

$$\mathrm{Q_t} = (1 - \sum_{\mathrm{m=1}}^{\mathrm{M}} \theta 1_{\mathrm{m}} - \sum_{\mathrm{n=1}}^{\mathrm{N}} \theta 2_{\mathrm{n}}) \bar{\mathrm{Q}} + \sum_{\mathrm{m=1}}^{\mathrm{M}} \theta 1_{\mathrm{m}} \, (\varepsilon_{\mathrm{t-m}} \varepsilon'_{\mathrm{t-m}}) + \sum_{\mathrm{n=1}}^{\mathrm{N}} \theta 2_{\mathrm{n}} \mathrm{Q_{t-n}}$$

$$\mathrm{R_t} = \mathrm{Q_t^{*-1} Q_t Q_t^{*-1}} \qquad (3.19)$$

Where $\bar{\mathrm{Q}}$ is the unconditional covariance of the standardized residuals resulting from the first stage estimation, and

$$\mathrm{Q_t^*} = \begin{bmatrix} \sqrt{\mathrm{q_{11}}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{\mathrm{q_{kk}}} \end{bmatrix} \qquad (3.20)$$

So that $\mathrm{Q_t^*}$ is a diagonal matrix composed of the square root of the diagonal elements of $\mathrm{Q_t}$. The typical element of $\mathrm{R_t}$ will be of the form $\rho_{\mathrm{ijt}} = \frac{\mathrm{q_{ijt}}}{\sqrt{\mathrm{q_{ii} q_{jj}}}}$.

3.2.5 Artificial Neutral Network

An artificial neural network is a category of information processing system that emulates the structure and functioning of the human brain through physical and mathematical approaches. The artificial neural network contains numerous units known as neurons. Each unit is linked to others, and each one is interconnected by a connection line. As data is input into the artificial neural network, it will propagate across the units, and then each unit will handle the data. In this situation, the units in ANN will attain an optimal state, referred to as training. Based on its fundamental operational mechanism, it is evident that with suitable training data, the neural network model can be effectively utilized to address challenges that are presently unsolvable. Owing to the unique configuration and computational methodology of neural networks, they have been widely utilized in image manipulation, robotics, knowledge extraction, and various other domains. The artificial neural network represents an advanced mathematical framework. It consists of numerous neurons connected by weights. The arrangement of neurons in the model is illustrated in Figure 3.1 underneath.

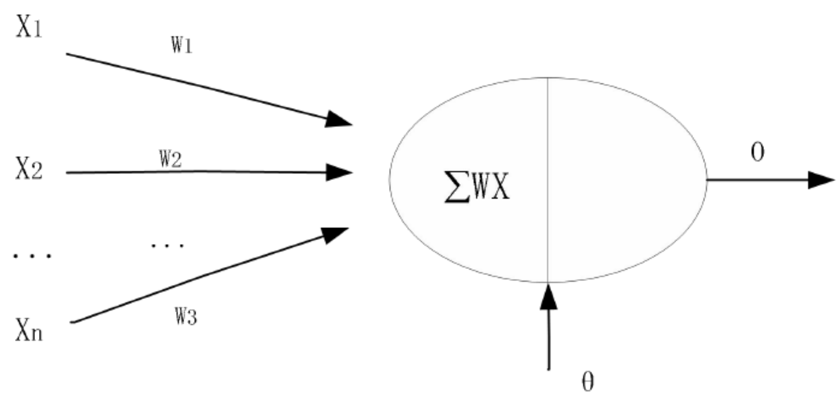

Figure 3.1 Structure of neurons

Each neuron has n inputs, which are transmitted by the connection of the weight W, and all the inputs $\sum_{i=1}^{n} W_i X_i$ received by the neuron will be linearly combined with the threshold term θ of the neuron, and afterward employ the activation function f to chart the linear amalgamation and result $O = f(\sum_{i=1}^{n} W_i X_i + \theta)$

The perceptron model is built on the basis of the neuron model, and the advent of the perceptron has triggered a research boom on the artificial neural network. The perceptron model is a two category model, and its structure is shown in Figure 3.2 as follows:

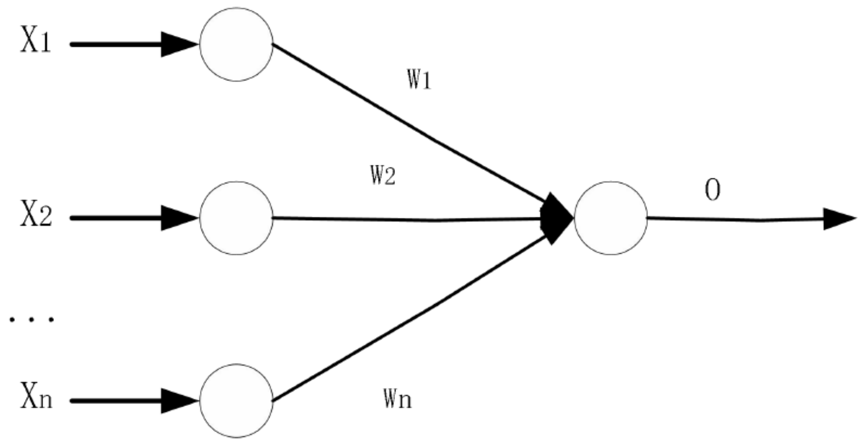

Figure 3.2 Structure of the perceptron model

The activation function implemented by the perceptron model is a basic step function, and its formula is shown in (3.21):

$$\operatorname{sgn}(x)=\begin{cases}1, x\ge 0\\ 0, x<0\end{cases} \tag{3.21}$$

Therefore, for a given input $x=(x_1,x_2,\dots,x_n)^T$, the connection weight between the input layer and the output layer is $w=(w_1,w_{2,}\dots,w_n)^T$. Combined with Equation (13), the output of the perceptron is shown in Equation (3.22).

$$y=\operatorname{sgn}(w^T,x)=\operatorname{sgn}(\sum_{i=1}^{n} w_i x_i) \tag{3.22}$$

Just like the original neural network, the single-layer perceptron network has a straightforward and uncomplicated structure, and requires minimal computation. Nevertheless, in subsequent research, individuals gradually recognized the limitations of this approach. For instance, when it comes to addressing non-linear issues, even if the activation function employs alternative complicated non-linear functions, it can solely solve problems that are linearly separable, and some essential functions cannot be attained. Thus its application becomes somewhat restricted. To address non-linear problems and improve the identification and categorization capabilities of neural networks, a multi-layer feedforward network is necessary, wherein an intermediate layer is introduced between the input and output layers to form a multi-layer feedforward perceptron network. In the midst of the 1980s, the backpropagation (BP) neural network algorithm was introduced. It comprises a multi-layer feedforward and reverse transmission structure, encompassing an input layer, hidden layer, and output layer. The BP neural network demonstrates exceptional capability in mapping high-dimensional functions and is adept at handling intricate classification challenges. It resolves the constraints of XOR (exclusive OR) that a simple perceptron cannot handle and integrates connections within concealed strata in a multi-stratum neural network. In recent times, there have been extensive discussions on employing neural networks for stock price prediction, including discussions on RBF neural networks, GA-BP neural networks, genetic LMBP neural networks, and neural networks combined with wavelets. Through ongoing research and exploration, the BP neural network proves effective in addressing concerns related to prediction, classification, and assessment.

The backpropagation (BP) neural network is currently among the most extensively utilized neural networks. The procedure utilizes the swiftest descent technique as the predominant learning principle and incorporates the retrograde propagation technique to modify the weights and thresholds, facilitating the objective function in reaching its minimum value. Generally, the BP neural network typically comprises three tiers, as illustrated in Figure 3.3 below, particularly the input stratum, concealed stratum, and output stratum. Although the quantity of nodes in the input and output strata is pre-established, the quantity of nodes and strata in the concealed stratum is adjustable, impacting the effectiveness of the BP neural network to a certain extent.

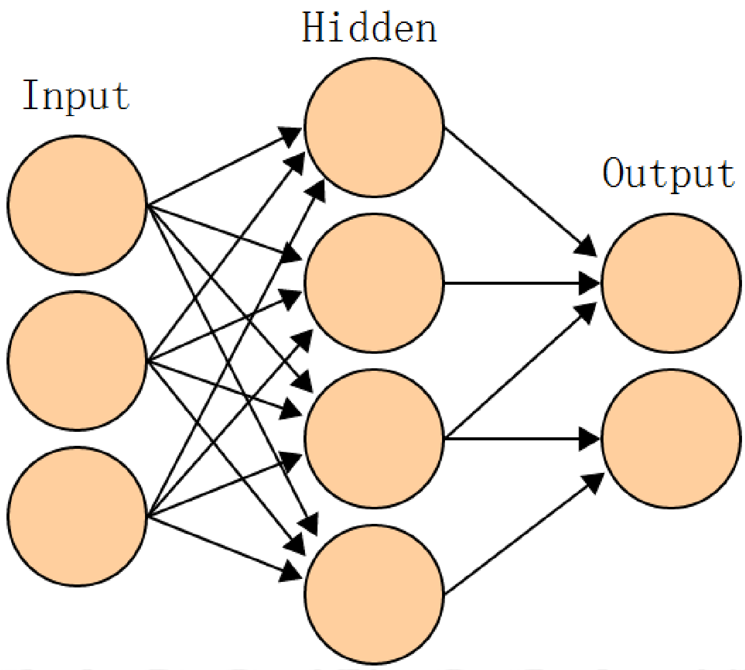

Figure 3.3 Structure of BP neural network

3.2.6 ANN-DCC-GRACH Model

The more reliable information available as input variables, the more accurate the predictions of the artificial neural network. The DCC-GARCH framework can capture dynamic associations and fluctuations, providing valuable insights in the analysis of financial markets (Yıldırım et al., 2022). Therefore, we are well-placed to utilize dynamic correlation and volatility as input variables for the artificial neural network approach. Bearing this in consideration, we amalgamate the ANN and DCC-GARCH frameworks and label them as the ANN-integrated DCC-GARCH model. The procedure for executing the model is delineated in the following steps.

(1) The data is divided into a training group and a prediction group.

(2) The DCC-GARCH framework is employed to calculate evolving associations, instabilities, and co-variances for the entire dataset. A single time period lag of all variables, including the evolving correlation, volatility, co-variance, as well as other indicators, are utilized as input factors in the training set, while the dummy variable for logarithmic returns acts as the output variable.

(3) All input variables along with the placeholder variables are normalized. (Kulkarni & Haidar, 2009). The standardization process is as follows:

$$X_{it} = \frac{x_{it} - \min(x_i)}{\max(x_i) - \min(x_i)} \tag{3.23}$$

where x_{it} represents the ith input variable at time t, and X_{it} standards for normalized values.

(4) A technique is employed to ascertain the quantity of concealed neurons. There is no direct approach to determine the quantity of neurons. (Rodriguez et al., 2022). Following (X. Li, 2008), the potential quantity of neurons is computed as follows:

$$l = \sqrt{m+n} + \alpha \tag{3.24}$$

where n is the number of nodes in the input layer, l is the number of nodes in the hidden layer, m is the number of nodes in the output layer, and α is a constant that belongs to (3.24).

(5) The resilient backpropagation with weight backtracking algorithm is employed to train ANN models with varying numbers of concealed layers. The optimal model is the one that demonstrates the highest precision in the training set. We determine the precision of prediction using the subsequent equation:

$$\mathrm{AP} = \frac{1}{T_1}\sum_{t=1}^{T_1}(I_{(\hat{P}_t > 0.5)} * I_{(r_t > 0)}) \tag{3.25}$$

where T_1 represents the number of training set samples, $\hat{P}_t$ is the estimated probability value, $I_{(r_t>0)}$ is an indicator function, and r_t is the log return. The higher the value of AP, the better the model. From this we can determine the optimal number of neurons, i.e. the best model.

(6) Ultimately, we employ the forecast dataset to the leading ANN model to predict the outcome. The empirical results in this study are obtained using the R Studio software. We predominantly utilized the "rugarch" and "neuralnet" packages in the R application. In the ANN models, we used the robust backpropagation with weight backtracking algorithm and the cross-entropy approach to calculate the convergence error. Within the ANN-DCC-GARCH model, associations related to BTC and the three assets (unrefined Oil, USD, and Gold), co-variance of BTC with the three assets, and instability of BTC

are normalized according to Equation (3.25). The single-time lag period data are considered as the input variables.

3.3 Summary

This section initially showcases the outcomes of the unit root examinations for BTC, Crude Oil, Gold, and US Dollar using the ADF test and PP test. Engle-Granger's examination for cointegration and the Granger Causality examination are utilized to explore the cointegration and causality connections between BTC and traditional financial assets. The subsequent phase of the paper utilizes the ARMA-GJR-GRACH model to elucidate the static correlation model between BTC and Gold and Oil. The third step of the article proposes a DCC-GARCH method with a neutral network, by providing historical information on correlations and risk spillovers with traditional financial assets and applying it to investment decisions in BTC. The next chapter describes the data selection and results, analyses for each of the three components separately.

CHAPTER 4

COMPARISON OF THE ASYMMETRIC RELATIONSHIP BETWEEN BTC AND GOLD, CRUDE OIL, AND THE U.S. DOLLAR BEFORE AND AFTER THE COVID-19 OUTBREAK

4.1 Brief Introduction

This section reveals the asymmetrical integration and asymmetrical causality between BTC and traditional financial assets (such as Gold, unrefined Oil, and the U.S. dollar) through data analysis. Their uneven associations are also examined by contrasting the data prior to and following the COVID-19 pandemic.

4.2 Data

Data on BTC, Aurum, crude Oil, and the United States Dollar Index (USDX) are obtained from Yahoo Finance. To ensure temporal synchronization, we collected weekly information from January 1, 2015, to June 15, 2023. Figures 4.1-4.3 depict the price trends of BTC and the previously mentioned three assets. It can be observed that the values of BTC and crude Oil show notable volatility, and there seems to be a certain association between their peaks and troughs, implying a phenomenon related to causation. In contrast, the USDX exhibits the smallest oscillations, followed by Aurum.

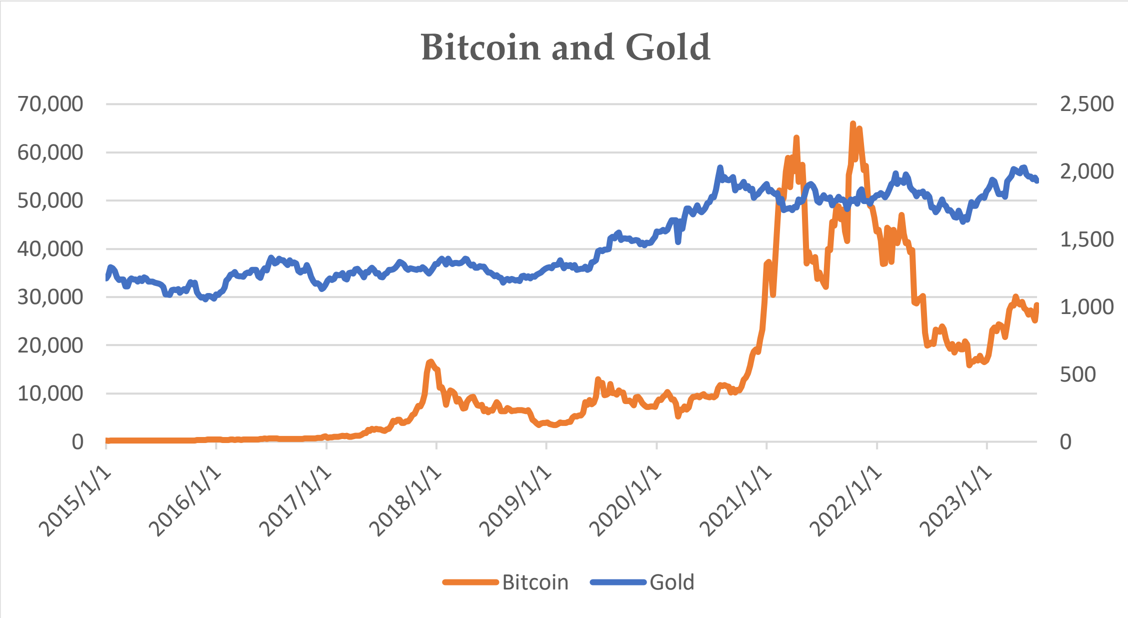

Figure 4.1 The price movement of BTC and Gold from January 2015 to June 2023

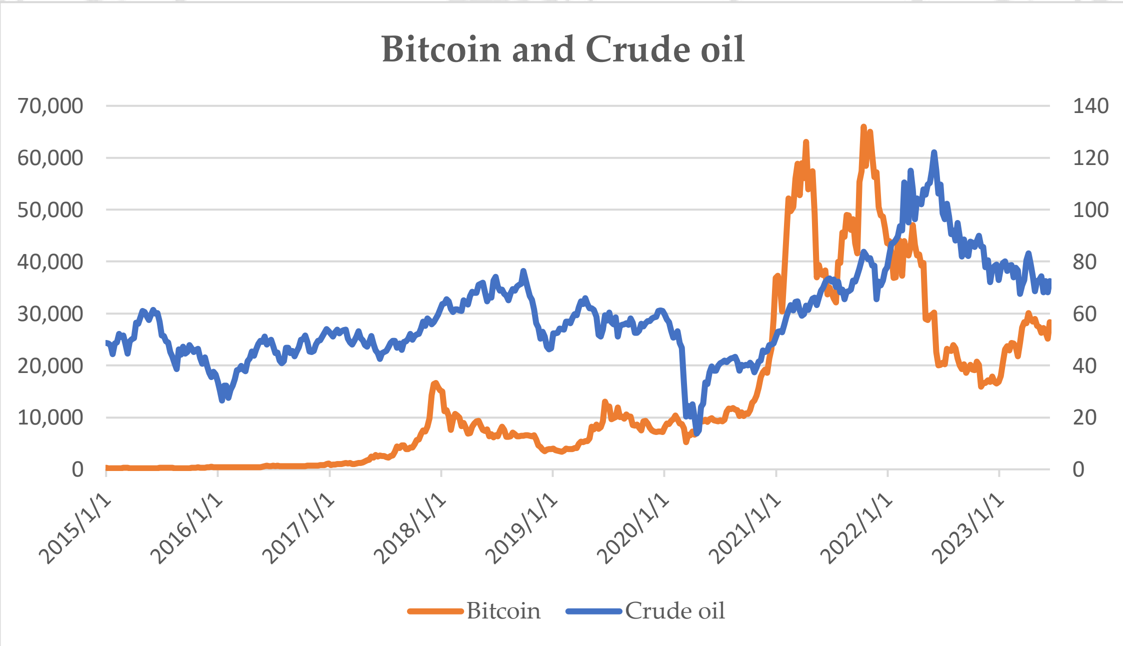

Figure 4.2 The price fluctuations of BTC and crude oil from January 2015 to June 2023

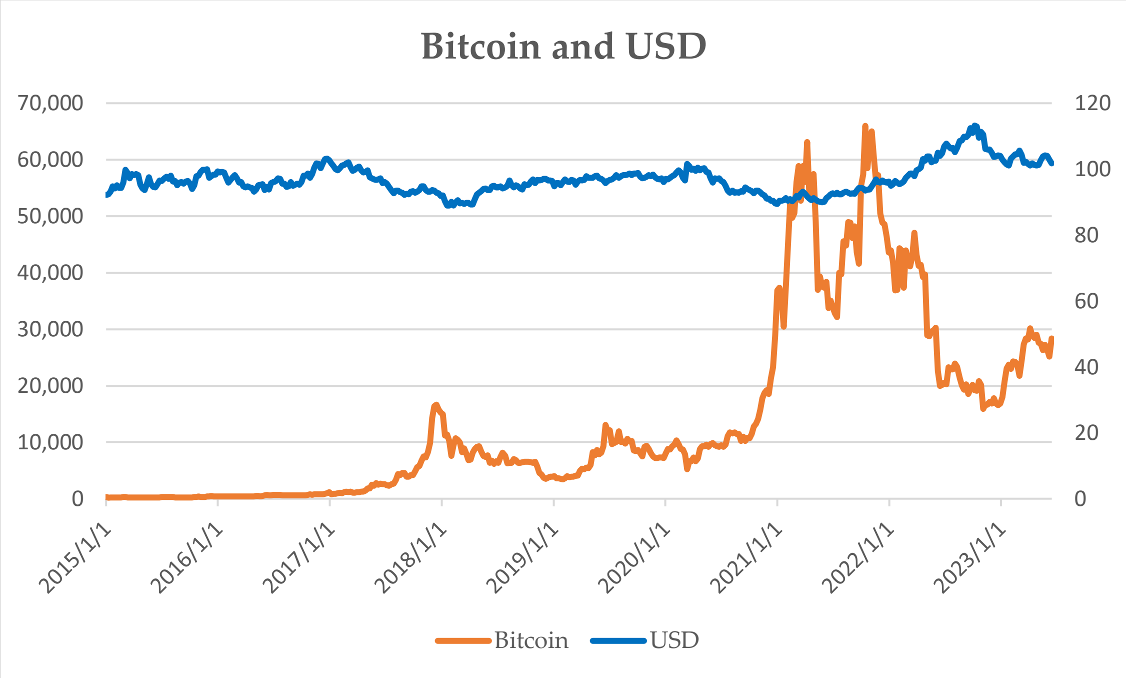

Figure 4.3 The price action of BTC and the U.S. dollar from January 2015 to June 2023

4.3 Empirical Analysis

This investigation aims to tackle two issues related to the asymmetrical prolonged connection between BTC and conventional fiscal resources, such as unrefined Petroleum, Aurum, and the American dollar, as well as the uneven causation between them. To handle the aforementioned inquiries, we initially take the natural logarithm of BTC and conventional fiscal resources and carry out unit root examinations. Subsequently, we employ the Engle-Granger methodology to evaluate the prolonged association between BTC and Petroleum, BTC and GOLD, and BTC and the American dollar, individually. Based on this, we explore the asymmetrical prolonged correlation between BTC and conventional fiscal resources. Lastly, we scrutinize the asymmetrical causation between BTC and conventional fiscal resources.

4.3.1 The Findings of Unit Root Tests

The table 4.1 presented illustrates the unit root analysis findings for BTC, unrefined Oil, Aurum, and the US dollar. ADF and PP methods are employed for these analyses. The null hypothesis for ADF and PP techniques suggests that the sequence possesses a unity root. It is noteworthy that none of BTC, unrefined Oil, Aurum, and the US dollar reject the null hypothesis at a 5% confidence level, indicating that the level data are all non-stationary. The outcomes of the unit root test for first-order difference data reveal that all first-order difference data reject the null hypothesis at a 1% confidence level, signifying that all first-order difference data are stationary. (Dyhrberg, 2016; Zhang et al., 2022) have also demonstrated that the natural logarithm of financial assets exhibits stationarity. Given this foundation, the ADF, PP, and KPSS approaches are employed to inspect the stability of the residuals with the natural logarithm of BTC as the dependent variable and traditional financial assets as predictors in regression analysis. If the test outcomes indicate stationarity, it implies the existence of a co-integration relationship between BTC and traditional financial assets. Table 4.2 presents the outcomes of the unit root analyses for the residuals. The ADF test utilizes the Bayesian Information Criterion (BIC) to choose the suitable lag length for the outcome variables. In the PP and KPSS examinations, the Newey-West self-adjusting technique is used to identify the bandwidth parameters (Newey & West, 1994). The zero hypothesis in both ADF and PP analyses postulates the existence of a unit root, whereas in the KPSS test, it implies that the data demonstrate stationarity. Clearly, the null hypothesis cannot be rejected in both ADF and PP tests, while it is rejected in the KPSS test. In other words, the three sequences of residuals do not display stationarity. Consequently, there is no co-integration or long-term association between BTC and the aforementioned three traditional financial assets. Some scholars endorse this viewpoint as well. For instance, certain academics have individually contested the prolonged connection between BTC and crude Oil, as well as between BTC and the US dollar (Ciaian et al., 2016; Ünvan, 2021). The connection between BTC and traditional financial assets is not enduring but intimate, encompassing, for instance, varying correlation over time (Bazán-Palomino, 2021), nonlinear correlation (Madichie et al., 2023), and spillover effect (Gkillas et al., 2022).

Table 4.1 Unit root tests of the BTC, Gold, crude Oil and US dollar

Level	ADF			PP		
Variables	None	intercept	trend	None	Intercept	trend
LogBTC	1.987	-1.812	-1.341	1.782	-1.776	-1.485
LogGold	1.052	-0.785	-2.919	1.150	-0.687	-2.828
LogOil	0.103	-2.284	-2.813	0.079	-2.505	-3.105
Logusd	0.451	-2.249	-2.360	0.464	-2.220	-2.327
1st Difference	ADF			PP		
Variables	None	intercept	trend	None	Intercept	trend
DlogBTC	-20.037***	-20.242***	-20.282***	-20.154***	-20.289***	-20.313***
DlogGold	-22.540***	-22.566***	-22.563***	-22.545***	-22.584***	-22.586***
DlogOil	-20.938***	-20.918***	-20.894***	-20.970***	-20.951***	-20.928***
Dlogusd	-20.405***	-20.390***	-20.367***	-20.404***	-20.388***	-20.364***

Note: *** denotes statistical significance at the 1% significance level.

Table 4.2 Unit root tests on residual series

	ADF	**PP**	**KPSS**
Gold	−2.215	−2.284	0.378 ***
Oil	−2.330	−2.528	0.382 ***
USD	−1.331	−1.473	0.335 ***

Note: *** denotes statistical significance at the 1% significance level.

Table 4.3 Unit root tests on residual series: tests for asymmetric cointegration for positive BTC

positive	ADF	PP	KPSS
Gold+	-0.950	-1.226	0.404*
Oil+	-0.782	-1.169	0.498*
usd+	-1.325	-1.602	0.219***
Gold-	-1.314	-1.408	0.398*
Oil-	-1.051	-1.557	0.296*
usd-	-2.102**	-2.309**	0.195

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels.

4.3.2 The Results of Asymmetric Cointegration and Causality Tests

In spite of the lack of co-integration between BTC and traditional financial assets, variations in traditional financial assets may have a lasting impact on BTC, whether positive or negative. Table 4.3 exhibits the outcomes of the asymmetric co-integration analysis between the affirmative/negative fluctuations of traditional financial assets and the positive fluctuation of BTC. Initially, only the US dollar - and BTC + are statistically significant at a 5% confidence level in ADF and PP tests. However, the KPSS test indicates that only the residual series of the US dollar - is not statistically significant. Hence, a non-linear enduring relationship exists between the negative fluctuation of the US dollar and the positive fluctuation of BTC. A decline in the USDX signifies an increase in the value of the currency, which acts as the underlying basis for BTC. Consequently, a decrease in the USDX will result in an increase in BTC's positive fluctuation (Oad Rajput et al., 2022). Moreover, there is no co-integration connection between the influence of Aurum and unrefined Oil, either positively or negatively, and the adverse impact on BTC. Table 4.4 illustrates the outcomes of the asymmetric co-integration analysis between the affirmative negative variations of traditional financial assets and the negative fluctuation of BTC. The ADF and PP examinations indicate that all remaining series are statistically significant, at a minimum, at a 10% confidence level. None of the KPSS examinations refute the null hypothesis. Therefore, there exists an asymmetric co-integration relationship between traditional financial assets (Aurum, unrefined Oil, the US dollar) and negatively fluctuating BTC. To elucidate, when BTC's value decreases, there is a co-integration relationship between Aurum, unrefined Oil, or the US dollar and BTC, irrespective of whether they appreciate or depreciate.

Table 4.4 Unit root tests on residual series: tests for asymmetric cointegration for negative BTC

negative	ADF	PP	KPSS
Gold+	-1.864*	-2.043**	0.183
Oil+	-1.800*	-2.013**	0.255
usd+	-2.824***	-2.777***	0.117
Gold-	-2.312**	-2.239**	0.289
Oil-	-1.635*	-1.748*	0.195
usd-	-2.427**	-2.315**	0.133

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels.

Table 4.5 displays the computation of the enduring relationship. Given that the variables comprise the overall positive or negative influence, the slope coefficient lacks practical significance. Nevertheless, the symbols and magnitudes of the slope coefficients still signify something. Initially, all the slope coefficients are statistically significant at a confidence level of 1%, confirming the existence of imbalance. Additionally, when compared to Aurum and unrefined Oil, the asymmetric impact of USDX on BTC is considerable. The decline in USDX, which corresponds to the increase in the US dollar's value, has the most pronounced effect on the elevation of BTC. This might be attributed to BTC being linked to the US dollar. It is also apparent that in contrast to the affirmative impact, the negative impact on traditional financial assets strongly influences the devaluation of BTC. As expected, the appreciation and devaluation of Aurum, unrefined Oil, and the US dollar produce disparate effects on the depreciation of BTC.

Table 4.5 Long-run relationships

positive	constant	s.e.	slope	s.e.
usd-	-1.243***	0.186	-13.379***	0.210
negative				
Gold+	0.213*	0.120	-4.033***	0.049
Oil+	0.116	0.121	-1.411***	0.015
usd+	1.348***	0.189	-9.343***	0.167
Gold-	0.725***	0.147	4.873***	0.066
Oil-	0.285*	0.143	1.494***	0.022
usd-	1.098***	0.208	9.610***	0.209

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels.

Examinations for multivariate normality and ARCH were initially conducted to assess the appropriateness of the Granger causality analysis. The results are presented in Table 4.6. The Jarque-Bera test indicated that BTC and all other assets do not adhere to a normal distribution. Additionally, the majority of multivariate ARCH tests refuted the null hypothesis, suggesting the potential presence of ARCH fluctuations in BTC and most financial assets. Consequently, traditional test methods for causality are not applicable. Table 4.7 displays the results of causality assessments using bootstrap simulations. Firstly, there is indication of Granger causality between unrefined Oil and BTC (but not Aurum or the US dollar). Secondly, an asymmetric causality is also observed between BTC and unrefined Oil, indicating a relationship between the adverse impact on unrefined Oil and the positive/negative fluctuation of BTC. However, there is no causality between Aurum/US dollar and BTC, irrespective of whether they undergo a positive or negative impact on BTC fluctuation.

Are there disparities in the uneven causality between BTC and traditional financial assets before and after the COVID-19 outbreak? Table 4.8 and Table 4.9 furnish the outcomes of the examination on uneven causality between BTC and traditional financial assets prior to and subsequent to the pandemic, respectively. The onset of COVID-19 did lead to modifications in the causality relationship between BTC and traditional financial assets. Pre-pandemic, a decline in Aurum prices would result in an upturn in BTC prices. There is no indication of Granger or uneven causality between unrefined Oil, the US dollar, and BTC. However, post-pandemic outbreak, the results in Table 4.9 align with those in Table 4.7.

Table 4.6 Tests for multivariate normality and ARCH in the VAR model

level	Jarque-bera	multivariate ARCH	VAR order
Gold	<0.001	<0.001	1
Oil	<0.001	<0.001	1
usd	<0.001	0.2261	1
positive	Jarque-bera	multivariate ARCH	VAR order
Gold+	<0.001	0.5173	1
Oil+	<0.001	<0.001	1
usd+	<0.001	0.6432	1
Gold-	<0.001	0.9757	1
Oil-	<0.001	<0.001	2
usd-	<0.001	0.01613	1
negative	Jarque-bera	multivariate ARCH	VAR order
Gold+	<0.001	<0.001	1
Oil+	<0.001	<0.001	1
usd+	<0.001	0.9664	1
Gold-	<0.001	0.9975	1
Oil-	<0.001	<0.001	2
usd-	<0.001	0.02565	1

Table 4.7 The results of tests for causality using the bootstrap simulations

null hypothesis	Test value	bootstrap p value
Gold does not Granger cause BTC	0.850	0.378
Oil does not Granger cause BTC	4.884	**0.018**
usd does not Granger cause BTC	1.288	0.268
Gold+ does not cause BTC+	0.410	0.716
Oil+ does not cause BTC+	0.075	0.850
usd+ does not cause BTC+	0.096	0.886
Gold- does not cause BTC+	0.528	0.712
Oil- does not cause BTC+	3.692	0.284
usd- does not cause BTC+	5.634	0.148
Gold+ does not cause BTC-	0.839	0.618
Oil+ does not cause BTC-	0.066	0.900
usd+ does not cause BTC-	0.066	0.890
Gold- does not cause BTC-	2.540	0.284
Oil- does not cause BTC-	2.590	**0.096**
usd- does not cause BTC-	2.196	0.312

Table 4.8 The results of tests for causality before the COVID-19 pandemics using the bootstrap simulations

null hypothesis	Test value	bootstrap p value
Gold does not Granger cause BTC	0.006	0.948
Oil does not Granger cause BTC	0.043	0.86
usd does not Granger cause BTC	0.081	0.786
Gold+ does not cause BTC+	3.851	0.24
Oil+ does not cause BTC+	2.751	0.338
usd+ does not cause BTC+	2.264	0.234
Gold- does not cause BTC+	5.966	**0.072**
Oil- does not cause BTC+	1.342	0.418
usd- does not cause BTC+	4.890	0.136

Table 4.8 The results of tests for causality before the COVID-19 pandemics using the bootstrap simulations (Cont.)

null hypothesis	Test value	bootstrap p value
Gold+ does not cause BTC-	2.099	0.49
Oil+ does not cause BTC-	1.133	0.578
usd+ does not cause BTC-	0.803	0.552
Gold- does not cause BTC-	1.717	0.356
Oil- does not cause BTC-	2.288	0.162
usd- does not cause BTC-	2.075	0.4

Table 4.9 The results of tests for causality after the COVID-19 pandemics using the bootstrap simulations

null hypothesis	Test value	bootstrap p value
Gold does not Granger cause BTC	0.490	0.518
Oil does not Granger cause BTC	5.354	**0.048**
usd does not Granger cause BTC	3.214	0.146
Gold+ does not cause BTC+	0.540	0.722
Oil+ does not cause BTC+	0.009	0.958
usd+ does not cause BTC+	0.014	0.958
Gold- does not cause BTC+	0.630	0.656
Oil- does not cause BTC+	6.362	0.014
usd- does not cause BTC+	1.786	0.334
Gold+ does not cause BTC-	0.035	0.886
Oil+ does not cause BTC-	0.003	0.956
usd+ does not cause BTC-	0.133	0.896
Gold- does not cause BTC-	1.736	0.27
Oil- does not cause BTC-	3.071	**0.056**
usd- does not cause BTC-	0.182	0.83

4.4 Conclusion

BTC remains highly sought after by investors. A comprehensive comprehension of the correlation between BTC and traditional financial assets is essential for investors and financial organizations. Utilizing existing research, asymmetric co-fluctuation and causality evaluations are employed to scrutinize the asymmetric co-fluctuation and causality between BTC and Aurum, BTC and unrefined Oil, and BTC and the US dollar. The outcomes of the testing are as follows: Firstly, employing the Engle-Granger co-fluctuation test, we ascertain that there is no co-fluctuation association between BTC and traditional financial assets. Secondly, there is a noteworthy co-fluctuation relationship between the adverse impact on the US dollar and the affirmative impact on BTC. Thirdly, there is a co-fluctuation association between a positive (negative) impact on traditional financial assets and a negative impact on BTC. Fourthly, there is Granger causality between unrefined Oil and BTC, in which a negative impact on unrefined Oil also leads to a negative impact on BTC. Lastly, there is no causality between Aurum/US dollar and BTC. These revelations elucidate the relationship between BTC and traditional financial assets from an asymmetric perspective and could assist in decision-making and risk mitigation for investments in BTC and traditional financial assets. However, this document, despite its findings in the asymmetric relationship between BTC and traditional financial assets, has its limitations. Both the asymmetric co-fluctuation test and asymmetric Granger causality test are static and cannot effectively illustrate the dynamic relationship between BTC and traditional financial assets. Additionally, the trends of BTC and traditional financial assets may have their own cycles. The co-fluctuation relationship or causality may vary with the economic cycles. Consequently, future studies are required to explore the dynamic relationship between BTC and traditional financial assets, as well as the co-fluctuation and causality in various time periods.

CHAPTER 5

DYNAMIC CORRELATION MEASUREMENT BETWEEN BTC, CRUDE OIL AND GOLD

5.1 Brief Introduction

This section utilizes the DCC-GARCH model to evaluate the dynamic linkage between BTC, petroleum, and valuable metal assets. The empirical results reveal that: (1) BTC demonstrates elevated risk in comparison to Gold and crude Oil, with Gold being the least risky. However, the risk for crude Oil was higher at the commencement of the COVID-19 pandemic. (2) The yield of BTC showcases an adverse correlation with risk, while the yield of Gold and crude Oil does not exhibit notable correlation with risk. (3) The correlation between BTC and crude Oil, as well as between BTC and Gold, manifests considerable instability. Specifically, the favorable correlation between BTC and crude Oil significantly amplifies at the initiation of the COVID-19 pandemic, while the unfavorable correlation between BTC and Gold intensifies during the same timeframe. These discoveries carry significant implications for peril administration, well-informed investment choices, and crisis hedging strategies.

5.2 Data

Many investors believe that compared with other financial investment products, BTC has the benefits of autonomy and decentralization, and will not be impacted by external economic fluctuations. In the uncertain global situation, BTC can be utilized as a tool to evade the impact of inflation and become a new generation of secure haven assets for risk management. More investors consider BTC as a new type of valuable metal. In comparison to BTC, traditional valuable metal lacks fluidity, but as a conventional hedging tool, it possesses numerous distinct advantages. Therefore, studying the relationship between BTC and valuable metal is of significant importance for evading risks, adjusting returns, and maintaining asset liquidity. Figure 5.1 illustrates the prices of valuable metal and BTC from November 24, 2013, to November 24, 2021. As can be observed from the figure, the price trend of valuable metal is very steady, while the price volatility of BTC is considerable, indicating that BTC is an asset with elevated yield, high speculation, and high volatility.

As a significant commodity marketplace, raw Petroleum marketplace not only plays a crucial role in worldwide economic functioning and international commerce but is also intimately associated with the financial market and has turned into a shared financial instrument. On one side, investors believe that large-scale goods such as raw Petroleum have the capability to withstand inflation in the long term and can be utilized to evade the impacts of inflation. On the flip side, the raw Petroleum marketplace price experiences substantial fluctuations, and "bottom reading" at the appropriate time can procure speculative gains. Furthermore, some academics have revealed that the raw Petroleum marketplace is closely connected to the Gold marketplace, and there might be a correlation between the two. Consequently, this article will also scrutinize the connection between BTC and the raw Petroleum marketplace and delve into the dynamic correlation between them. Figure 5.2 shows the price changes of raw Petroleum and BTC from November 24, 2013, to November 24, 2021. The price alteration tendency of the two indicates that the fluctuation of raw Petroleum marketplace price is more visible, and there is a pronounced declining direction from November 24, 2013, to April 19, 2020, with prices rising from April 20, 2020, to November 24, 2021. Based on the aforementioned analysis, the price instability of the raw Petroleum marketplace, BTC marketplace, and Gold marketplace is sequentially diminished.

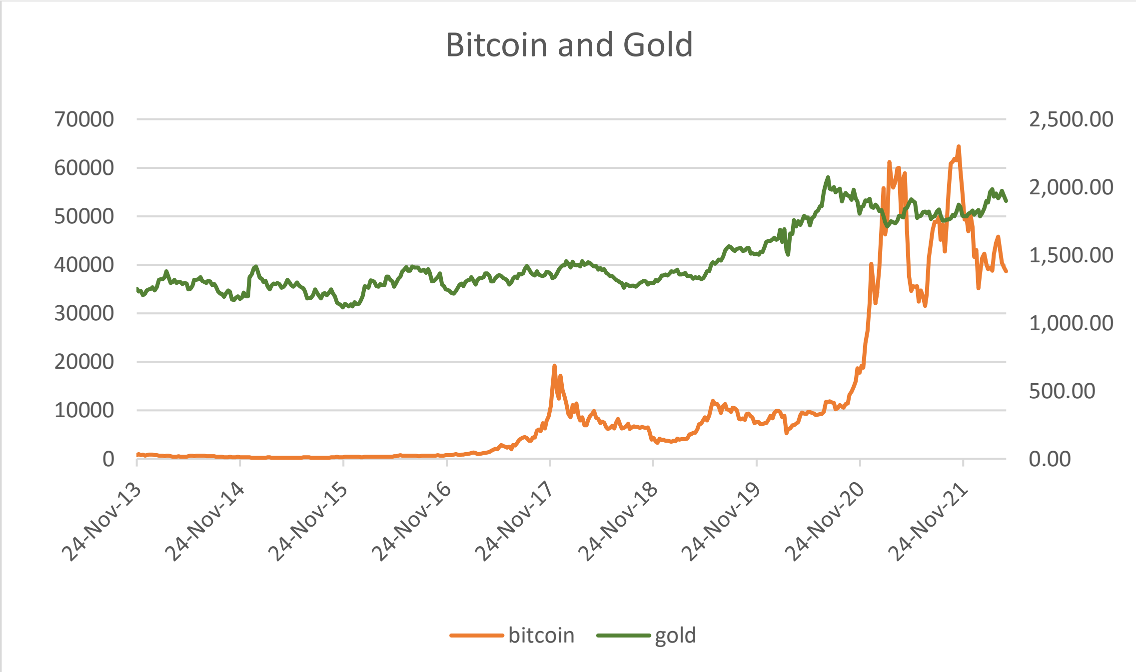

Figure 5.1 The valuations of BTC and Gold

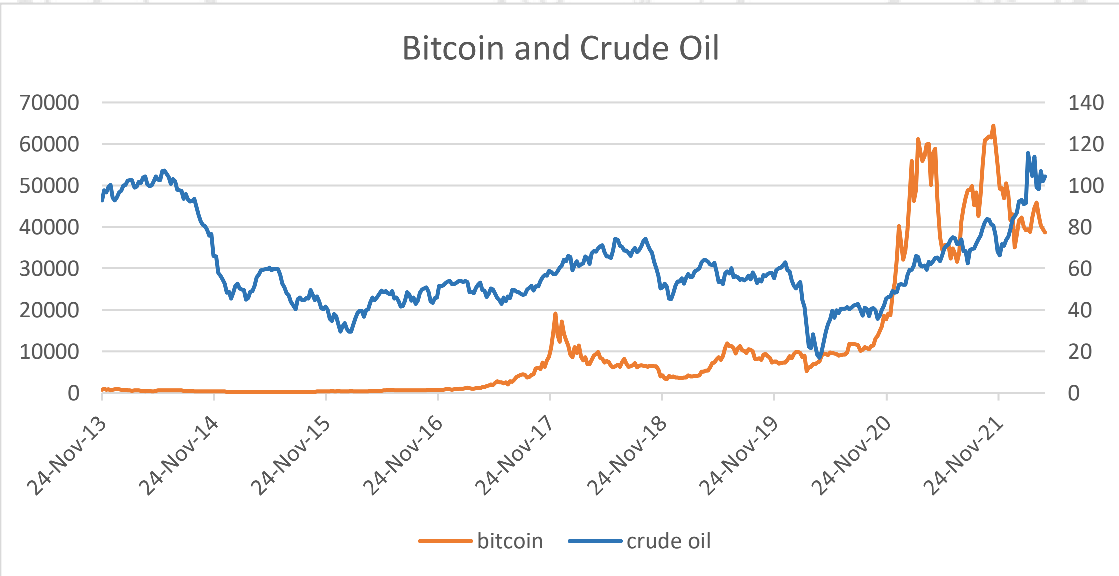

Figure 5.2 The values of BTC and Crude Oil

In order to examine the dynamic correlation between BTC and two important financial assets, crude Oil and Gold, this study selects the weekly yield statistics of NYSE BTC stock price, Gold future price, and crude Oil future WTI price as the research index.

Among them, the yield utilizes the logarithmic yield of the closing price, and the sample investigation period is from January 2014 to April 2022. The data is from Investing. com. The instability of the yields of BTC, crude Oil, and Gold from 2014 to 2022 is depicted in Figure 5.3. Overall, the instability of BTC and crude Oil is very intense, while the instability of Gold is very minimal, indicating that Gold is an asset with more steadfast yield. Specifically, BTC has high jeopardy and robust volatility in the two years from 2017 to 2018, which may be connected to the Fed's interest rate increase and the phased reinforcement of the US dollar, which amplified trans-border capital flows and drew away from market liquidity. It is noteworthy that in the initial phase of the COVID-19 outbreak, crude Oil displayed a higher risk, and its risk fluctuation even surpassed that of BTC.

Table 5.1 illustrates the fundamental descriptive statistical properties of BTC, crude Oil, and Gold. It is observable that the mean weekly logarithmic return rate of the three assets is more than 0, and the highest average return rate of BTC is 0.008796, but its standard deviation is also the largest, indicating that the hazard is also the supreme. The average yield of Gold surpasses that of crude Oil, but the standard deviation is notably lower than that of crude Oil, indicating that Gold is a more consistent investment over the long term. The asymmetry of BTC and crude Oil is under 0, and the kurtosis is above 3, signifying a peak and heavy-tailed phenomenon. Table 5.2 delineates the correlation coefficients between the three financial assets of BTC, crude Oil, and Gold, elucidating the connection between the three. In general, the association between the three financial assets is affirmative, indicating that the three perils change in the same direction. Among them, the correlation coefficient between BTC and crude Oil is the most potent, reaching 11.51%, indicating that the bond between BTC and crude Oil is the sturdiest. Subsequently, crude Oil and Gold exhibit a correlation coefficient of 8.38%, and BTC and Gold depict the weakest bond, at only 4.99%.

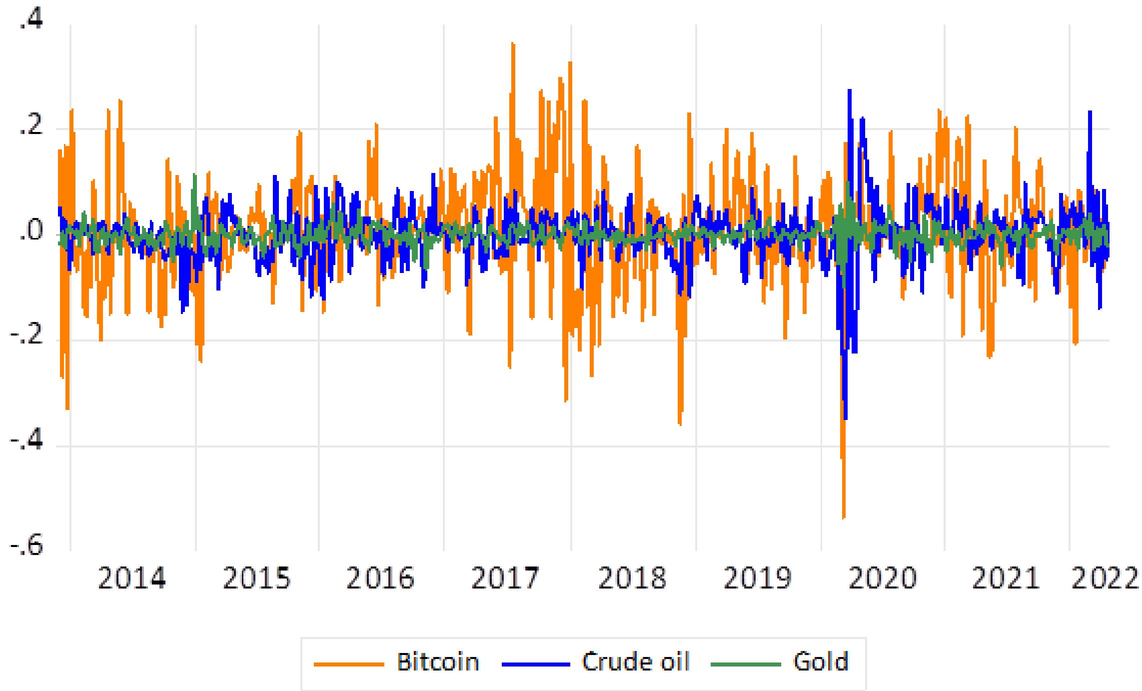

Figure 5.3 Log returns of BTC, Crude Oil and Gold

Table 5.1 Data descriptive and statistics

	BTC	Crude Oil	Gold
Mean	0.008796	0.000267	0.000949
Median	0.007207	0.003809	0.001517
Maximum	0.363420	0.275756	0.112555
Minimum	-0.536031	-0.346863	-0.098970
Std. Dev.	0.107931	0.057744	0.020281
Skewness	-0.308070	-0.501723	0.247949
Kurtosis	4.979572	9.073209	7.466234
Jarque-Bera	78.62373	693.0854	369.3666
Probability	0.000000	0.000000	0.000000
Observations	439	439	439

Table 5.2 Pairwise correlations of BTC, Crude Oil and Gold

Correlation Probability	BTC	Crude Oil	Gold
BTC	1.0000		

Crude Oil	0.1151	1.0000	
	(0.0158)	-----	
Gold	0.0499	0.0838	1.0000
	(0.2960)	(0.0803)	-----

5.3 Empirical Analysis

5.3.1 Estimate results of GJR-GARCH in Mean models

The Table 5.3 presents the calculated outcomes of GJR-GARCH in Mean models for the three financial assets. Parameter b signifies the volatility of three financial assets σ Influence on their corresponding yields. The table demonstrates that solely the B predictor of BTC is noteworthy at the 1% confidence level, suggesting that the volatility of BTC is adversely linked with its yield, and for each increment in the volatility of BTC, the yield diminishes by approximately 29.39%. There is no conspicuous connection between the volatility and yield of crude Oil and Gold.

The symbol α denotes the effect of the short-term influence of the three financial assets on their respective instability. As evident from the table, the association between BTC and Gold α The computed figure is affirmative and substantial at the 1% and 5% confidence levels, respectively, implying that when BTC and Gold encounter short-term impact, their instability will notably rise; Yet, for crude Oil α The estimation outcomes are insignificant, signifying that the short-term influence on crude Oil does not have a noteworthy impact on its volatility.

The symbol γ represents the influence of leverage effect on three financial assets. As demonstrated in the table, the value of BTC γ is adverse and substantial at the 1% confidence level, suggesting there is a significant leverage effect in BTC price variations; meaning that the change in BTC price fluctuation caused by the same degree of negative information is more substantial than that caused by positive information. The estimate γ of crude Oil is positive and substantial at the 1% confidence level, indicating an important anti-leverage effect in crude Oil price fluctuation; this means the adjustment of crude Oil price fluctuation caused by the same degree of positive information is more substantial than that caused by negative information. The estimated γ of Gold is adverse and significant at the 10% confidence level, signifying there is also a certain leverage effect in the fluctuation of Gold price.

The symbol β signifies the continuity of risk oscillations of three financial assets. As depicted in Table 5.3, the computed β of the three financial assets are all affirmative, with the highest estimation for BTC and the lowest estimated value for crude Oil, denoting that the endurance of BTC risk fluctuation is the most robust, followed by Gold, and the persistence of crude Oil risk fluctuation is the most feeble.

Table 5.3 Estimated results of GJR-GARCH in Mean models

GARCH in Mean	BTC	Crude Oil	Gold
b	-0.2939** (0.1473)	0.1550 (0.1545)	-0.0758 (0.3166)
c	0.0392*** (0.0141)	-0.0048 (0.0068)	0.0025 (0.0059)
Variance equation			
ω	0.0002* (0.0001)	0.0003*** (0.0001)	0.0002* (0.0001)
α	0.0946*** (0.0265)	0.0205 (0.0426)	0.1794** (0.0794)
γ	-0.1056*** (0.0275)	0.3324*** (0.1099)	-0.1741* (0.0944)

Table 5.3 Estimated results of GJR-GARCH in Mean models (Cont.)

GARCH in Mean	BTC	Crude Oil	Gold
β	0.9424*** (0.0119)	0.7064*** (0.0745)	0.7519*** (0.0991)
DoF	4.8903*** (1.0449)	6.4217*** (1.5431)	5.6414*** (1.4306)
Loglikelihoood	401.2147	721.6235	1124.084
AIC	-1.7959	-3.2556	-5.0892

Note: *, **, *** represent 10%, 5%, and 1% significance level, respectively.

As illustrated in Figure 5.4, the volatility measure of BTC demonstrates a gradual pattern prior to 2017, signifying a consistent decline in BTC's volatility over time. This trend may be attributed to the increasing acceptance of BTC as a financial instrument, with companies such as Dell, Microsoft, and Las Vegas casinos in the United States beginning to adopt BTC, and the emergence of platforms like Coinbase focusing on BTC payments. From the end of 2017 to the beginning of 2018, the volatility measure of BTC reached its peak, possibly due to the excessive surge in BTC prices resulting from the significant influx of speculators into the BTC market, prompting widespread government crackdowns on BTC in numerous countries, including China, India, the Netherlands, and others. It is noteworthy that the onset of the COVID-19 pandemic in 2020 did not substantially impact the volatility measure of BTC, suggesting that BTC exhibited a certain risk-averse effect in the early stages of the COVID-19 pandemic.

It is evident from Figure 5.5 that between 2014 and 2022, the volatility measure of crude Oil has remained relatively constant and maintained a low level, with a substantial fluctuation observed only around April 2020. This occurrence may be attributed to the severe impact on global transportation, manufacturing, and industrial operations following the onset of the COVID-19 pandemic in 2020. This led to a sharp decline in the demand for crude Oil, while Oil-producing countries such as the United States and Russia were unable to promptly reduce crude Oil supply. This resulted in a significant imbalance between crude Oil supply and demand in the global market, with the uncertainty surrounding the pandemic causing panic among crude Oil traders, subsequently leading to a drastic drop in crude Oil futures prices, thereby instigating a sudden increase in crude Oil volatility.

Observing Figure 5.6, it becomes apparent that between 2014 and 2022, the volatility measure of Gold remained relatively constant, experiencing only two significant fluctuations in early 2015 and 2020. The substantial risk variations observed in early 2015 might be attributed to the gradual tapering of the quantitative easing policy in the United States, sustained global deflationary pressures, and measures by the Indian government to curb Gold consumption. The heightened risk fluctuation of Gold in 2020 could be attributed to the global COVID-19 crisis, economic turmoil, political upheaval, social anxiety, subsequent erratic movements in financial markets, and a surge in investors' appetite for risk mitigation.

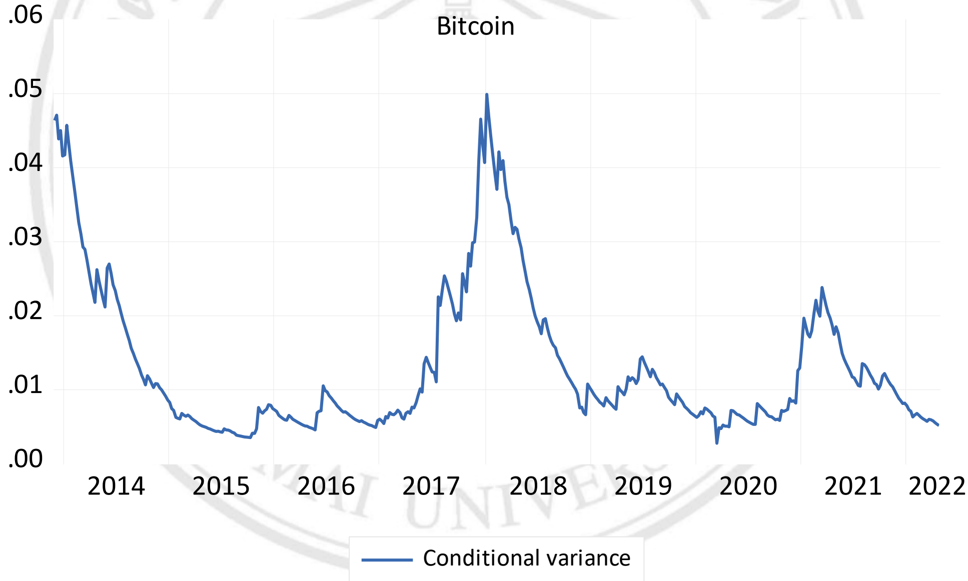

Figure 5.4 Conditional variance of BTC

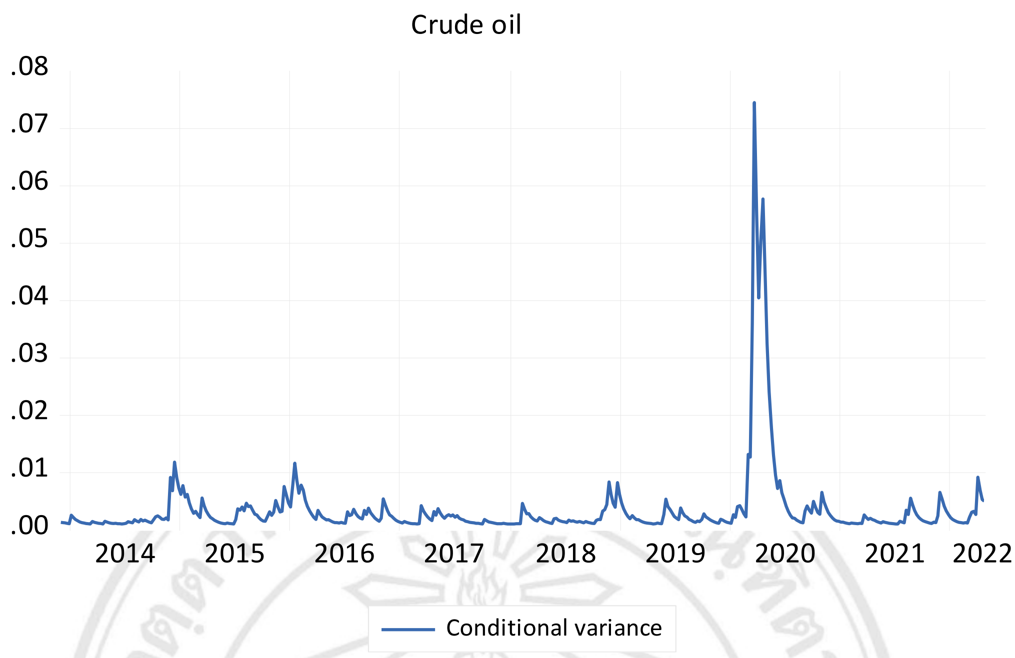

Figure 5.5 Conditional variance of Crude Oil

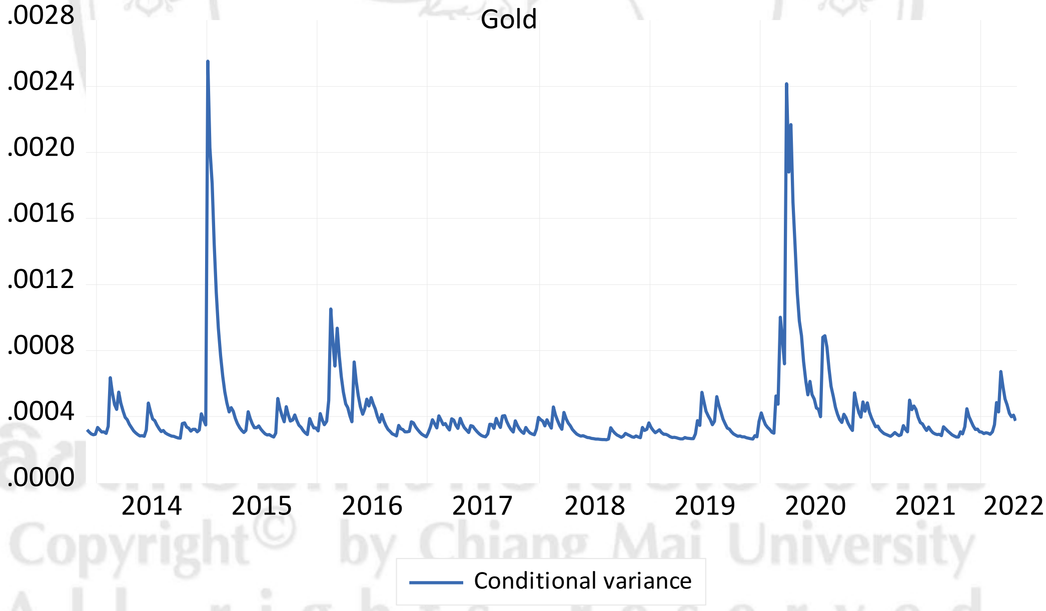

Figure 5.6 Conditional variance of Gold

5.3.2 The estimated results of dynamic correlation

Image It is clear from Figure 5.7 that the relationship between BTC and crude Oil exhibits notable volatility. Throughout most of the observation period, the two display alternating positive and negative correlations. This suggests that over the long term, the connection between BTC and crude Oil is generally feeble, with little evidence of a strong positive correlation during simultaneous rises and falls, or a strong negative correlation between them. However, influenced by market conditions, it is possible that a strong correlation between BTC and crude Oil may emerge in specific short cycles. The image clearly indicates that during the early stages of the COVID-19 pandemic, BTC and crude Oil demonstrated a pronounced positive correlation, which persisted for a period of time. During this period, the demand for crude Oil plummeted and BTC weakened. In the context of extraordinary events like the COVID-19 pandemic, the financial market is fraught with high uncertainty and risk. To mitigate the impact of the portfolio, investors should closely monitor the role of BTC. BTC, characterized by high returns and high risk, has the potential to offer substantial decentralized income for the portfolio.

Image 5.8 depicts that the connection between BTC and Gold also displays noticeable fluctuations, with alternating positive and negative correlations between them. BTC can be considered as a safeguarding asset for Gold. Over a broader research cycle, there is minimal correlation between BTC and Gold. Additionally, BTC and Gold showcase varying degrees of correlation within different market environments. Most of the time, BTC is utilized for diversified investment purposes to attain higher risk-adjusted returns. In times of extreme events, both BTC and Gold can act as safeguarding assets to mitigate financial risks. The image unmistakably indicates that in the early stages of the COVID-19 pandemic, BTC and Gold exhibited a strong negative correlation. During this time, Gold performed robustly, while BTC weakened. Amid extraordinary events, Gold still serves as a conventional and effective safeguarding tool, capable of hedging against inflation. Over a prolonged period, the alternating correlation between the two demonstrates that both BTC and Gold can function as risk-mitigating tools. Within the portfolio, BTC can serve as a substitute for Gold to achieve higher risk-adjusted returns.

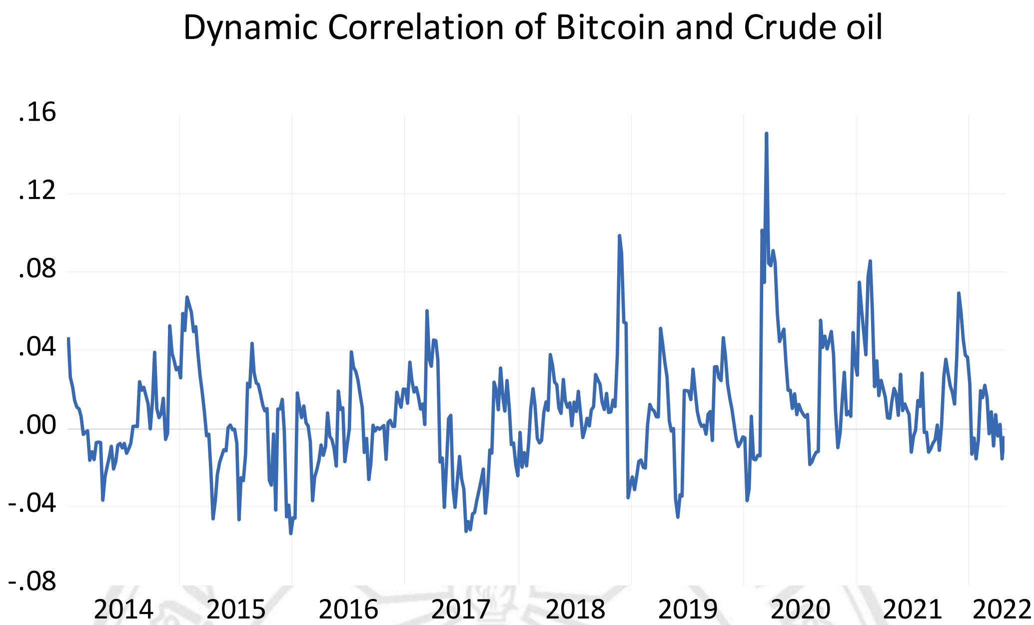

Figure 5.7 Dynamic correlation between BTC and Crude Oil

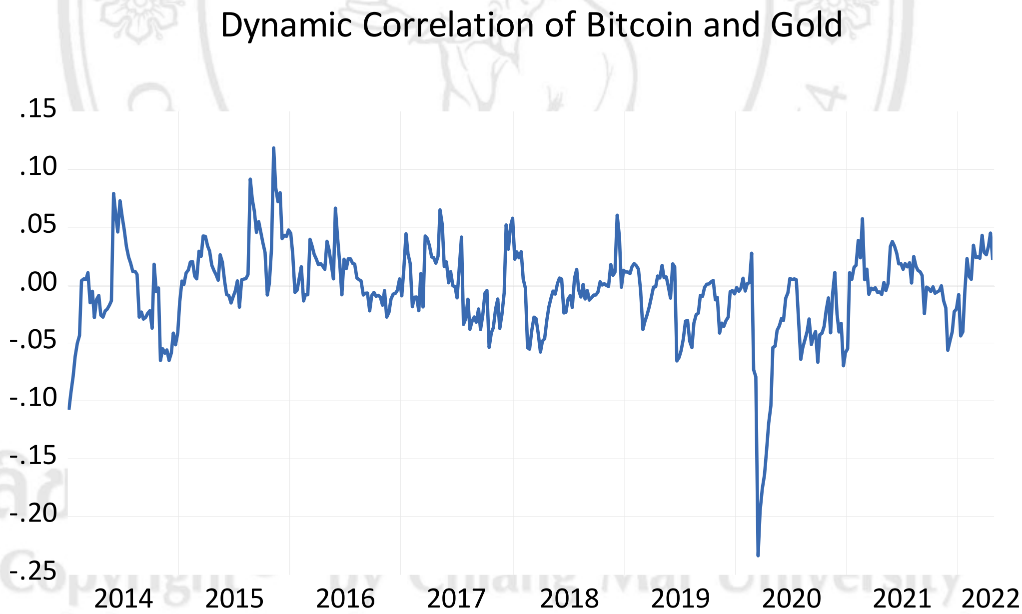

Figure 5.8 Dynamic correlation between BTC and Gold

5.4 Conclusion

In this section, the DCC-GARCH model is used to assess the dynamic connection between BTC and crude Oil, BTC and Gold, with the incorporation of the COVID-19 epidemic phase. The investigation in this paper is to some degree advantageous to investors and financial institutions for investment and risk management of BTC, crude oil, and Gold. The study affirms that BTC has an alternating positive and negative correlation with Gold i.e. BTC can be considered as a sheltering asset for Gold. At the onset of the COVID-19 outbreak, BTC showed a pronounced reverse correlation with Gold, while BTC displayed a significant reverse correlation with crude Oil. Owing to the COVID-19 outbreak, global trade and energy demand diminished in the first half of 2020. This could be the cause for the positive correlation between BTC and crude Oil. Within this time frame, the price of Gold rose, resulting in a negative correlation between BTC and Gold. In general, BTC is more precarious than crude Oil and Gold. Nonetheless, in the event of a hazard in crude Oil, it represents the riskier asset for BTC.

CHAPTER 6

DO THE CORRELATION AND VOLATILITY BETWEEN BTC AND TRADITIONAL FINANCIAL ASSETS HELP TOWARD INVESTMENT DECISIONS? AN ANN-DCC-GARCH APPROACH

6.1 Brief Introduction

BTC is also a high-risk, high-return financial asset (amid the COVID-19 pandemic, in 2021, the value of BTC surpassed $68,000 per token. And by the conclusion of 2022, the BTC price dropped beneath $20,000 again (Yahoo Finance, 2022). As evident, the value of BTC is extremely unstable. This is the reason numerous bettors and financial institutions are eager to fund in BTC. Bettors are very intrigued in making accurate investment choices or more accurately anticipating the value of BTC.

6.2 Data

Figure 6.1 BTC prices from Sept. 2014 to Dec. 2022

At various points, BTC trading choices should be altered. Figure 6.1 demonstrates the everyday closing values for BTC from 2014 to 2022. Following the onset of the COVID-19 outbreak, BTC is in an upward market from 2019 to early 2021, while the BTC market transitions to a full downward market from the second part of 2021. BTC values regress to 2020 levels. This indicates that BTC is an extremely high-quality investment asset up to 2021. Evidently, investors in BTC should embrace a distinct investment approach before and after the COVID-19 pandemic. It is very logical to expect that BTC investors and financial institutions are keen to generate more gains in upward markets and minimize investment risk in downward markets. Hence, how should investors make BTC investment choices in different time periods? Is it feasible to accomplish this anticipation through a projecting methodology? These are the inquiries that need to be tackled in this research.

The information in this article was acquired from the Wind database. The data is daily, and the time range spans from September 17, 2014 to December 23, 2022. Input factors encompass everyday highs, lows, and commencement values for BTC, in addition to binary factors for Gold, US dollar, and crude Oil. A 0 denotes a decrease in value, and a 1 signifies an increase in price. All input factors have a one-period lag. Save for the binary factors, all variables are normalized using the entropy weight method. The information for 2019 is considered as ex post data before the emergence of COVID-19, while the data for 2022 is ex post subsequent to the outbreak of COVID-19.

Table 6.1 presents the data description for the whole sample, as well as the sub-samples of 2019 and 2022. It is evident that the average value in 2019 is 7383.25 and 28355.82 in 2022, indicating a substantial alteration in the BTC price before and after the COVID-19 outbreak. The price volatility of BTC is also substantial, as demonstrated by the minimum and maximum values in both 2019 and 2022.

Table 6.1 The data descriptive and statistics

BTC	total sample	Subsample in 2019	Subsample in 2022
Mean	12860.64	7383.25	28355.82
Median	7106.54	7853.04	23222.24
Maximum	67566.83	13016.23	47465.73
Minimum	178.10	3399.47	15787.28
Std. Dev.	16197.13	2656.19	10183.79
Skewness	1.54	-0.057687	0.44
Kurtosis	4.28	1.80	1.55
Observations	2134	258	254

6.3 Empirical Analysis

The experimental findings in this research were computed using the R Studio application. We primarily employed the "rugarch" and "neuralnet" bundles in the R tool. In the ANN models, we applied the resilient backpropagation algorithm with weight backtracking and the cross-entropy method to assess the convergence error. In the ANN-DCC-GARCH model, correlations between BTC and the three assets (crude Oil, USD, and Gold), covariance of BTC with the three assets, and BTC's volatility are normalized in accordance with Equation (3.25). The input variables are based on data from the previous period.

6.3.1 Estimate results of the DCC-GARCH models

Figure 6.2 depicts the fluctuating correlation between BTC and established financial assets, specifically Gold, crude Oil, and the US dollar. It is evident that the relationships between BTC and Gold, BTC and crude Oil, and BTC and the US dollar display a distinct dynamic pattern. BTC and Gold, as well as BTC and crude Oil, are predominantly characterized by favorable correlations. The correlation between BTC and Gold is marginally greater than the correlation between BTC and crude Oil for the majority of the time frame. This observation was substantiated by (Gkillas et al., 2022). BTC and the U.S. dollar exhibit an inverse correlation, which notably intensifies in 2020 and 2022. These discoveries aid in the evaluation of BTC and conventional financial asset portfolios. Nevertheless, solely relying on correlation estimates does not enable a thorough examination of BTC investment choices.

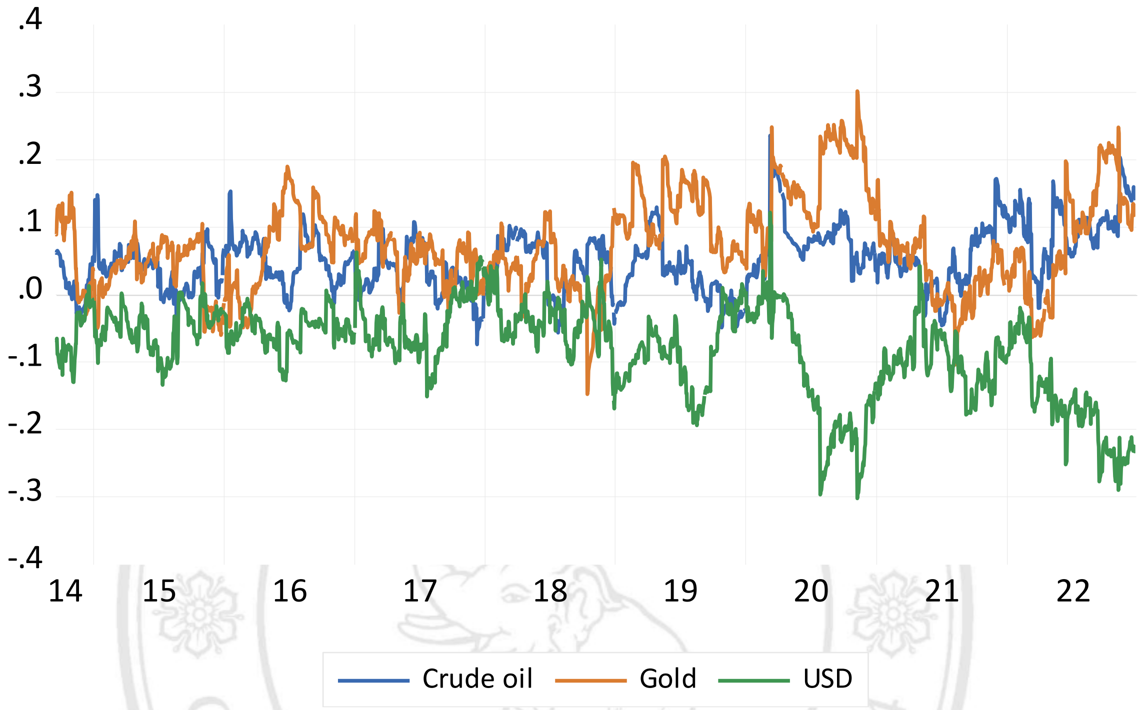

Figure 6.2 Pairwise correlations between BTC and Gold, crude Oil and USD

Figure 6.3 displays the instability of BTC and the co-movement of BTC with traditional financial assets. It is evident that BTC experiences significant instability, especially in 2017 and 2020. Smales (2019) and Long et al. (2021b) also evidence that BTC has a greater volatility than Gold. In 2020, the correlation between BTC and Gold, as well as BTC and crude Oil, is notably more robust, potentially due to the onset of the COVID-19 pandemic. Specifically, the correlation between BTC and crude Oil undergoes substantial fluctuations in 2020. The correlation between BTC and the U.S. dollar demonstrates a consistent strengthening pattern from year to year, with the most significant strengthening observed in 2022.

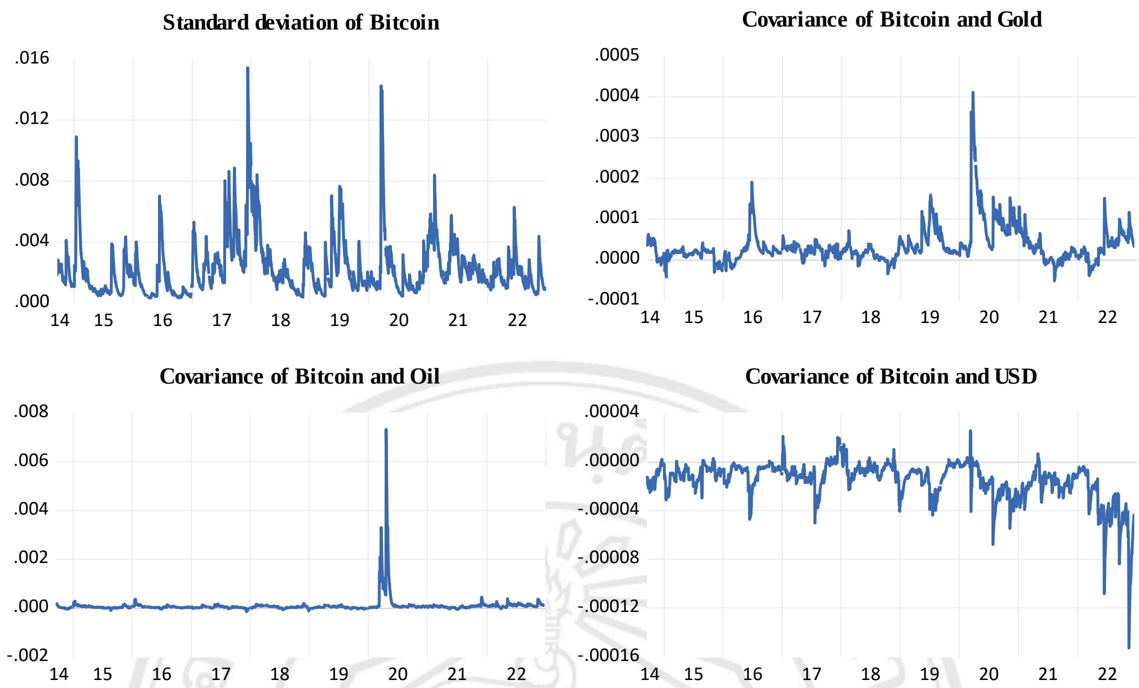

Figure 6.3 Volatility of BTC and covariance between BTC and the traditional financial assets

6.3.2 Prediction analysis of the ANN-DCC-GARCH models

We use the fluctuating correlation and covariance derived from the DCC-GARCH model as input variables in the ANN model to assess the predictive capacity of the ANN-DCC-GARCH model on BTC transactions. To evaluate whether the outcomes of the DCC-GARCH model contribute to the ANN predictions, we construct four models. Model 1 is an ANN model that does not incorporate the estimated results of the DCC-GARCH model. Model 2 is an ANN model that includes only covariance as input variables. Model 3 is an ANN model that includes only dynamic correlation as input variables. Model 4 is an ANN model that incorporates both dynamic correlation and covariance as input variables. Initially, we fit the four models using data from two separate in-sample sets, and then select the number of hidden layers of the ANN model and the best models based on the prediction error. Subsequently, we compare the fit accuracy of the four models within the two in-sample sets based on the goodness-of-fit, specifically the fitting accuracy. Furthermore, we use each of the four models to project BTC trading decisions for out-of-sample data and compute the cumulative returns. Finally, we compare the cumulative returns in 2019 and 2022 for different risk preferences with the aid of the best ANN-DCC-GARCH model.

Figure 6.4 illustrates the fitting inaccuracies of the four models for varying quantities of concealed layers. We compute the smallest and largest quantities of concealed layers based on (Ibnu Choldun R.et.al, 2020). The range of hidden layers for Model 1 is from 3 to 13, and for the other models, it is from 4 to 14. It is evident that the fitting error varies slightly for different quantities of hidden layers, and there are substantial differences in the fitting errors among the four models. As the number of hidden layers increases, the fitting error for each model generally decreases. In the in-sample data from 2014-2018, we determined that the optimum number of hidden layers for Model 1 and Model 2 is 13, while for Model 3 and Model 4 it is 14. In the in-sample data from 2014-2021, we established that the optimal number of hidden layers for Model 1 is 12, and for the other models, it is 14. Based on the minimal fitting error, Model 4 emerges as the best-fitting model. This also underscores the utility of correlation and covariance in predicting BTC transactions. Furthermore, it indirectly confirms the appropriateness and soundness of the ANN-DCC-GARCH model.

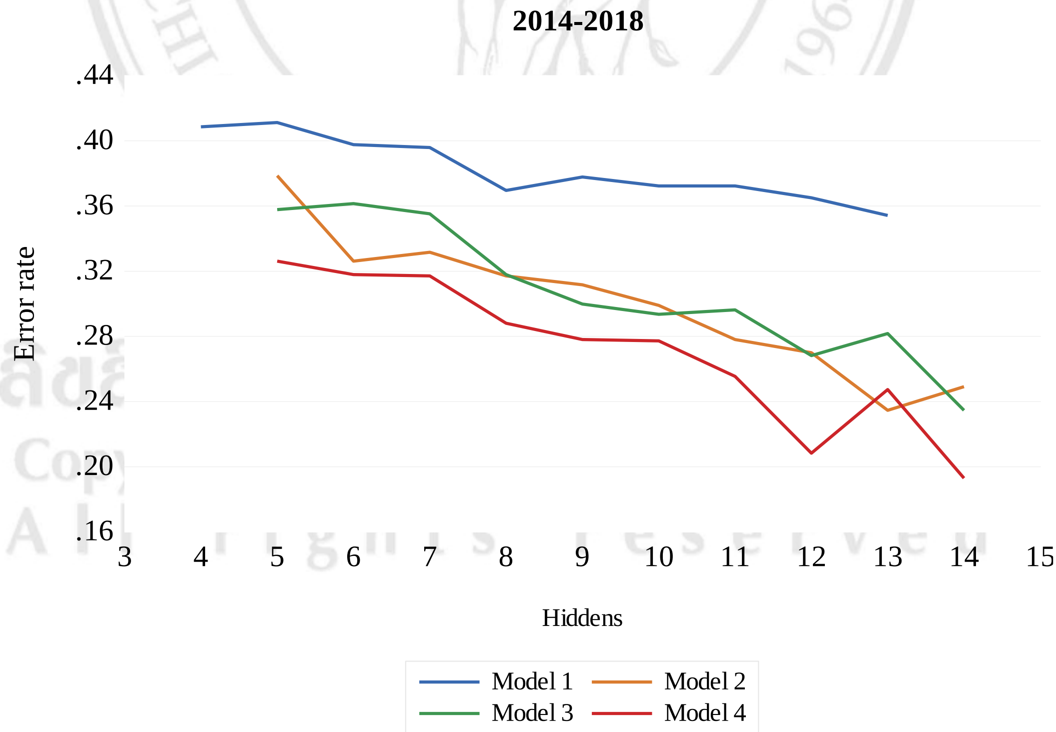

Figure 6.4 (a) Error rates at different numbers of hidden neurons for the 2014-2018 dataset

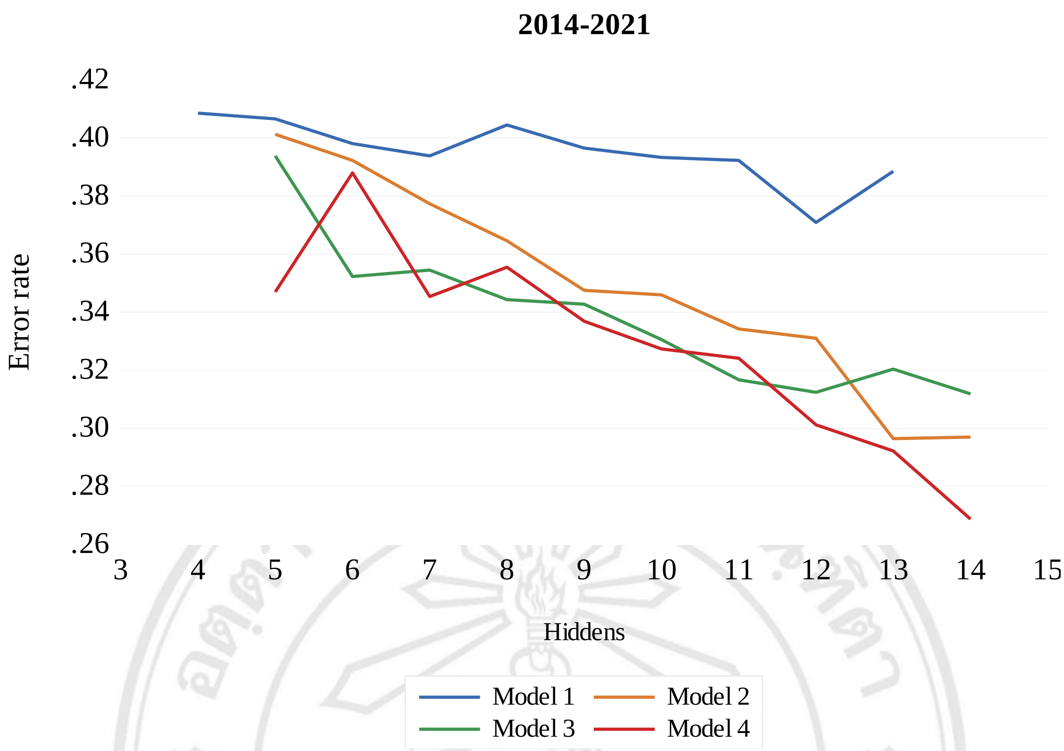

Figure 6.5 (b) Error rates at different numbers of hidden neurons for the 2014-2021 dataset

Table 6.2 displays the fitting accuracy of the four models. It is evident that in the 2014-2018 sample, Model 4 achieves an accuracy of over 80% and accurately predicts the upward trend with an 87.38% accuracy. In the 2014-2021 sample, the accuracy of Model 4 is 73.12%, with the prediction of the upward trend reaching a high accuracy of 85.18%. Comparing the four models reveals that Model 2, Model 3, and Model 4 all outperform Model 1, demonstrating that the information derived from the DCC-GARCH model contributes to effective BTC trading forecasts.

Table 6.2 Goodness of fit of ANN, ANN-DCC-GARCH models for BTC

Periods	Models	Accuracy rate	Accuracy rate for buying	Accuracy rate for selling
2014-2018	Model 1	0.6458	0.7656	0.4980
	Model 2	0.7654	0.8230	0.6943
	Model 3	0.7654	0.8328	0.6822
	Model 4	0.8071	0.8738	0.7247
2014-2021	Model 1	0.6291	0.8126	0.4116
	Model 2	0.7036	0.7782	0.6151
	Model 3	0.6881	0.7792	0.5802
	Model 4	0.7312	0.8518	0.5884

Figure 6.5 forecasts the trading returns for BTC in 2019 and showcases the cumulative trading returns for long-term investment, Models 1-4, and two arbitrary investment strategies. Notably, Model 4 yields a cumulative return of 318%. To elaborate, an initial investment of $1 million at the commencement of 2019 could potentially generate a return of $3.18 million by the year's end. Among all the models, Model 4 delivers the most accurate predictions, affirming the practicality of the ANN-DCC-GARCH model. Furthermore, the decision to opt for long-term holding can yield a return of 192%, suggesting that the BTC market experienced a bull market in 2019. This is further validated by the profitability of the two random investment strategies. Additionally, Model 2 and Model 3 can be profitable with returns of 189% and 266%, respectively, indicating that dynamic correlation information is particularly advantageous for BTC investment decisions.

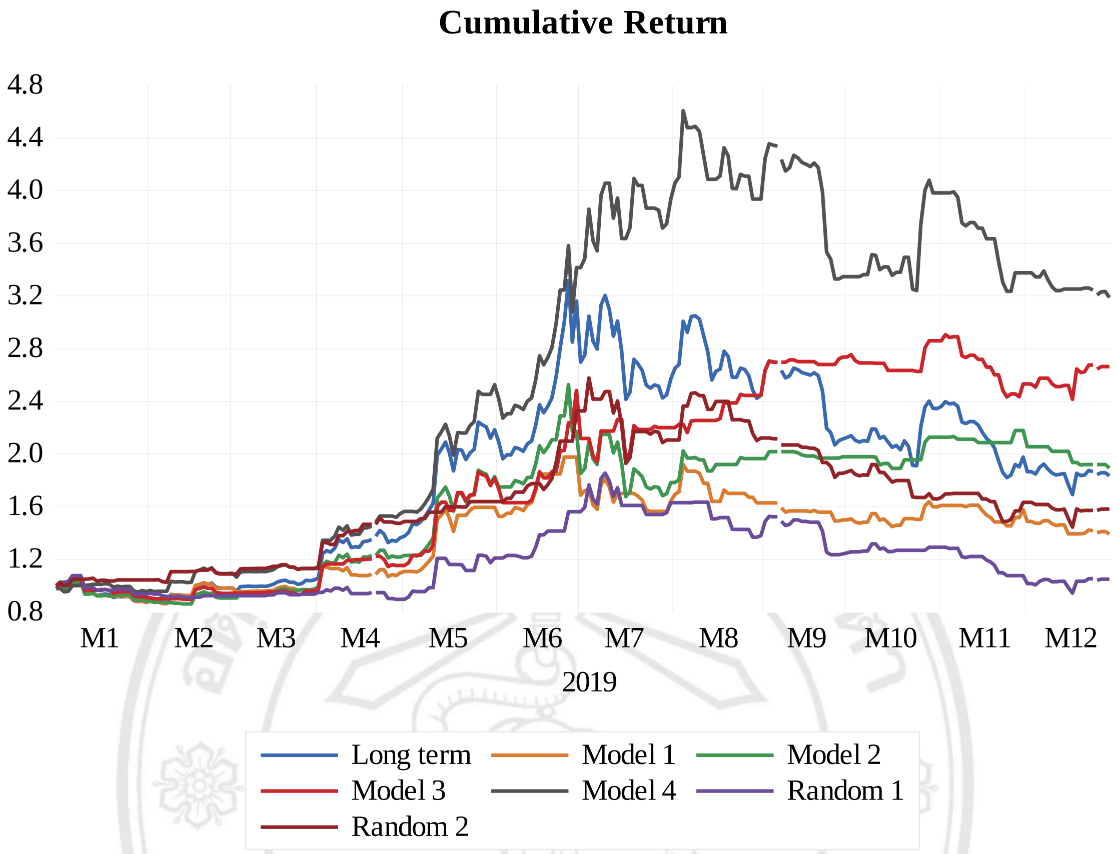

Figure 6.5 Predicted return of BTC in 2019 (before the COVID-19)

Figure 6.6 depicts the anticipated trading returns for each model in 2022. The BTC market is experiencing a bear market in 2022 amid the COVID-19 epidemic, escalating energy prices, and the Russian-Ukrainian war. It is projected that long-term BTC holdings will incur approximately a 64% loss. Conversely, investment strategies utilizing Models 1-4 would notably mitigate the percentage loss. For instance, Model 4 forecasts a cumulative return of 84.8%, and Model 2 86%, substantially higher than the 36% loss for long-term holdings. This underscores the efficacy of the ANN-DCC-GARCH models in diminishing investment losses during the bear market phase in BTC. Notably, two random investment strategies surpass long-term holdings, highlighting the imprudence of the latter strategy during a bear market period.

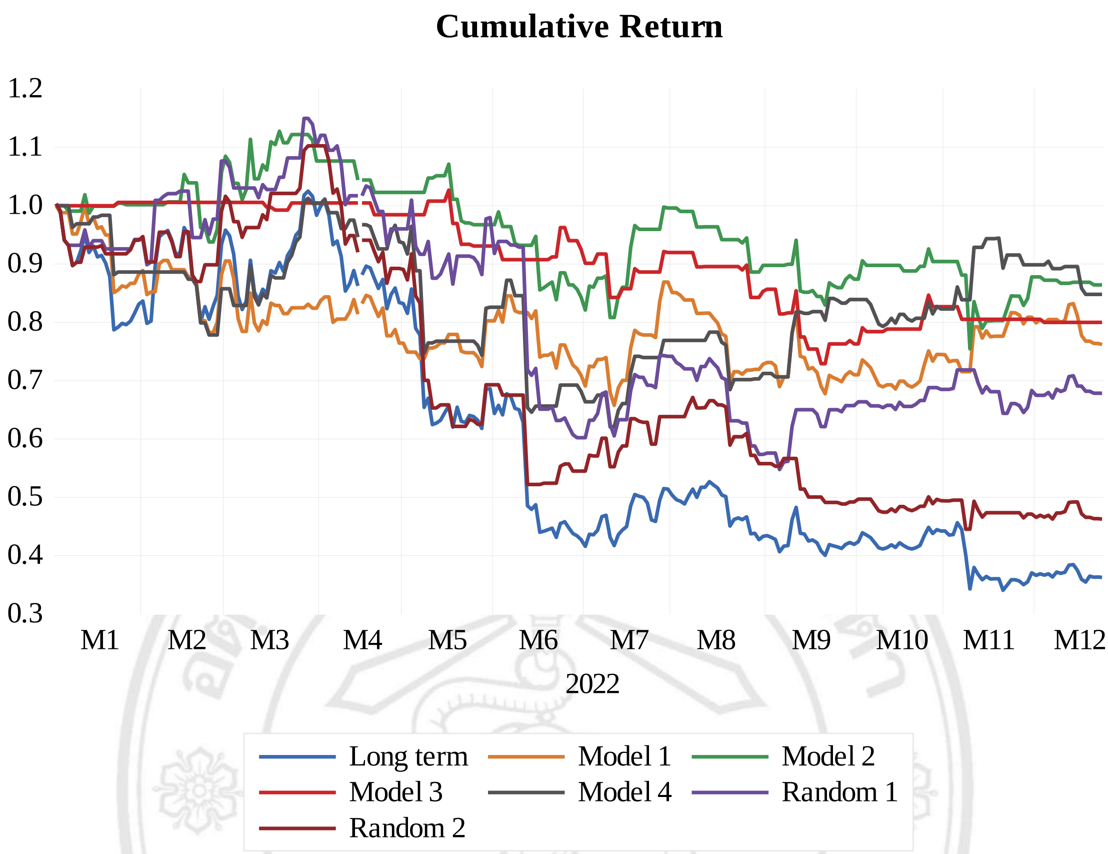

Figure 6.6 Predicted return of BTC in 2022 (during the COVID-19)

In the aforementioned investment assessment, we employ a forecasted probability above 50% as a purchase and a probability below 50% as a no-trade. However, varying levels of risk tolerance lead to distinct preference settings. Thus, we utilize 50% as the risk-neutral preference, 20% as the risk-seeking preference, and 80% as the risk-averse preference. Figure 6.7 illustrates the weekly cumulative returns for the three risk preferences and long-term holdingsin 2019. Evidently, the risk-neutral approach proves the most profitable in 2019. Both risk-averse and risk-seeking investors yield smaller returns than risk-neutral individuals but higher returns than long-term holders. This outcome suggests that adopting a risk-neutral stance is the optimal strategy during BTC's bullish market phase. Figure 6.8 showcases the cumulative returns in 2022 for the three risk preferences and long-term holdings. It can be observed that during the bear market phase in 2022, risk-averse individuals can transform a loss into a gain of approximately 20%. The analysis presented in Figure 6.7 and Figure 6.8 reaffirms the practicality of the ANN-DCC-GARCH model.

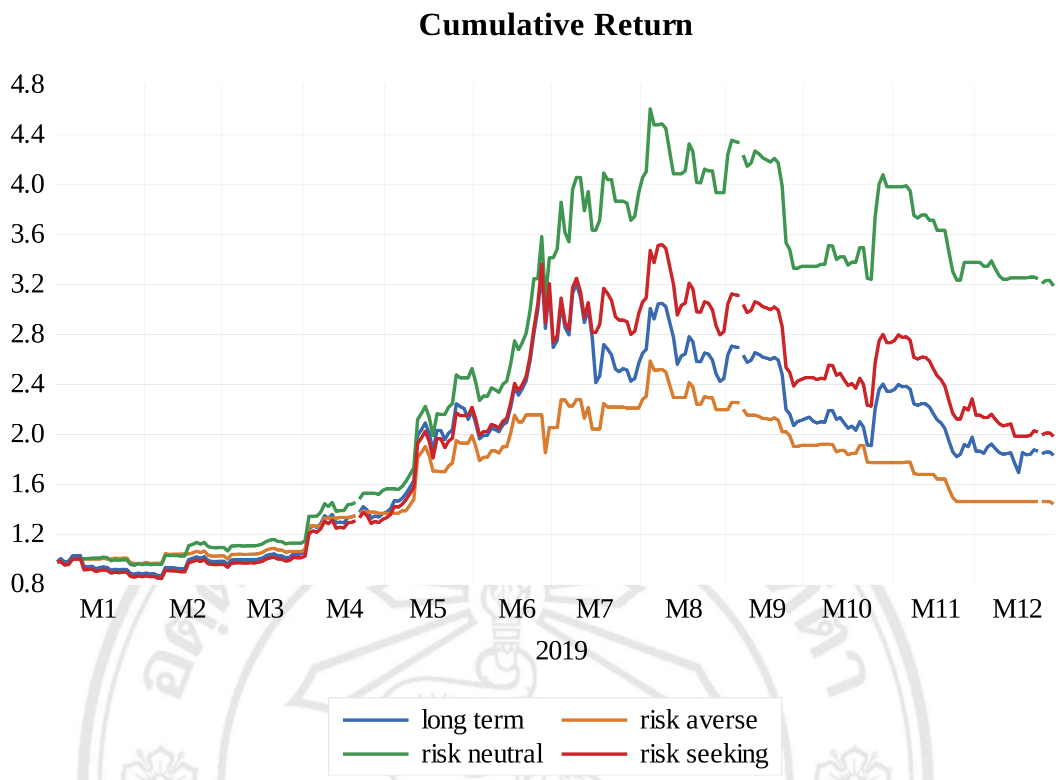

Figure 6.7 Weekly cumulative returns of BTC for different risk preference in 2019

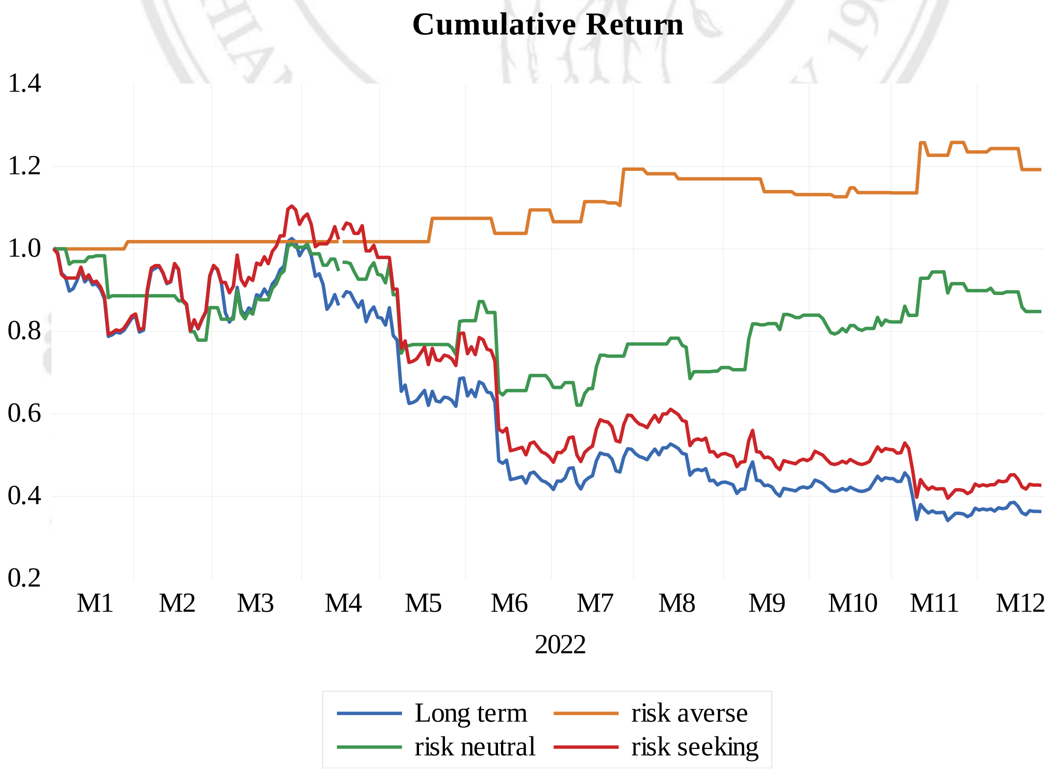

Figure 6.8 Cumulative returns of BTC for different risk preference in 2022

6.4 Conclusion

The BTC market has drawn a significant number of investors, leading to a growing need for the development of investment approaches. Therefore, in this document, we introduce an ANN-DCC-GARCH model that combines econometric and machine learning models for the first time to aid in BTC investment trading decisions. Additionally, we make predictions for BTC investment trading strategies before and after the outbreak of COVID-19.

The forecasted results for BTC demonstrate that the ANN-DCC-GARCH model is both practical and operational, and it also confirms the superiority of the ANN-DCC-GARCH model over the ANN model. Numerous researchers utilize the DCC-GARCH model to examine the dynamic correlation and volatility of financial assets and provide investment recommendations based on these findings. The ANN-DCC-GARCH model underscores the significant role of dynamic correlation and volatility in investment decisions, while also directly quantifying the investment trading strategies for financial assets.

Before the COVID-19 outbreak, specifically during 2019, the investment trading strategy based on the ANN-DCC-GARCH model yielded a return of 318%. This demonstrates the robust predictive capability of the ANN-DCC-GARCH model during the bullish market phase of BTC, enabling it to capture excess profits. Furthermore, during the bearish phase of BTC, the ANN-DCC-GARCH model assists investors in mitigating substantial losses. Additionally, the ANN-DCC-GARCH model can tailor different investment strategies for individuals with varying levels of risk tolerance. We observe that a risk-neutral approach is ideal during the bullish phase of BTC, while a risk-averse approach is preferable during the bearish phase.

CHAPTER 7

CONCLUSIONS AND FUTURE RESEARCH

Cryptocurrency is one of the fastest growing digital currencies globally. The success of the initial cryptocurrency, BTC, signified a rapid increase in market capitalization, leading to the emergence of other types of cryptocurrencies. Cryptocurrencies are built on blockchain technology. Blockchain technology differs significantly from the conventional centralized institutional system controlled entirely by a single organization. Due to the distinctive characteristics of BTC and its underlying blockchain technology, governments, policymakers, and numerous investors, traders, and portfolio managers are keen on market analysis and forecasting techniques. The fluctuations in BTC's price are impacted by various factors, and we have incorporated traditional financial assets closely linked to BTC, such as Gold, the U.S. dollar, and Oil, to enhance the precision of our predictions. By using their static and dynamic correlations, machine learning techniques are integrated to forecast BTC. Moreover, machine learning techniques have recently gained prominence in numerous scientific and social science domains due to their capacity to recognize patterns in historical data and identify non-linear associations between variables. Therefore, this study opts for novel approaches in BTC price prediction and, for the first time, proposes the DCC-ANN-GRACH model applied to BTC price forecasting. This section outlines the present research, offers some policy suggestions, and provides recommendations for future endeavors.

7.1 Summary of the Study

The current research introduces the BTC price forecasting issue and its implications in the new economy. The initial section gives a brief overview of digital currencies, BTC, and prediction techniques from conventional to emerging machine learning methods. Subsequently, the study's issue, methodology, and content are introduced. Section 2 presents a review of literature for this research, covering fundamental concepts of cryptocurrencies, BTC, and blockchain, pertinent theoretical underpinnings of BTC forecasting, the correlation between BTC and traditional financial assets (Gold, Oil, and U.S. dollar), and discusses related research in the existing literature on the BTC price prediction challenge. Section 3 offers a systematic review of data selection, cleansing, and validation used in this study's cryptocurrency prediction issue. The various techniques applied in this study, including the emerging machine learning model ANN and traditional models (OLS, ARIMA, and GARCH), are presented, and the empirical results are featured in Section IV. The empirical findings of this study consist of four segments:

In the initial segment we choose data obtained from Yahoo Finance on BTC, Gold, Crude Oil, and the U.S. Dollar Index. To ensure temporal coherence, we utilize weekly data from January 1, 2015 to June 15, 2023. The findings reveal that the price fluctuations of BTC and the three assets, BTC and crude Oil are more unstable and the peaks and troughs exhibit a certain correlation, which could indicate a causal relationship. In contrast, the US Dollar Index displays the least variability, followed by Gold. The historical price of BTC, acting as a technical indicator, anticipates a similar price as indicated by the technical analysis in the existing literature review. Another outcome of this empirical investigation is that machine learning models perform better, unlike numerous authors who still uphold the superiority of traditional statistical models in price prediction.

In the second section, the study assesses the dynamic correlation between BTC and Crude Oil, and BTC and Gold utilizing the DCC-GARCH model integrating the COVID-19 pandemic phase. The weekly yield data of the NYSE BTC stock price, Gold futures price, and crude Oil futures WTI price are chosen as the research indicators. In this scenario, the logarithmic return of the closing price is employed for the yield, and the sample period scrutinized is from January 2014 to April 2022. The data is procured from Investing.com. BTC's two years of heightened risk and volatility from 2017 to 2018 could be related to the Fed's rate hike as well as the eventual strengthening of the U.S. dollar and the surge in cross-border capital flows, which drained liquidity from the market. It's noteworthy that at the onset of the COVID-19 pandemic, BTC exhibited a strong negative correlation with Gold, whereas BTC displayed a strong positive correlation with Crude Oil. Due to the COVID-19 pandemic, there was a decrease in international trade and energy demand in the first half of 2020. This could account for the positive correlation between BTC and Crude Oil. Meanwhile, the price of Gold surged during this period, leading to a negative correlation between BTC and Gold. In general, BTC possesses more risk compared to Crude Oil and Gold. However, in the case of a risk associated with Crude Oil, it is a riskier asset than BTC. This provides a beneficial approach for managing risk and portfolios amidst future risk phases.

The third section, for the BTC price forecasting problem. The BTC market draws a large number of investors, and how to devise a BTC investment approach becomes a concern for investors. Hence, this paper chooses the Wind database under the concept of combining econometric model and machine learning model. The data are daily data, and the sample period is from September 17, 2014 to December 23, 2022. Input variables encompass the daily peak, bottom, and opening prices of BTC, as well as binary variables for Gold, the U.S. dollar, and crude Oil. 0 signifies a price decrease and 1 signifies a price rise. All input variables are delayed by one period. All variables except binary variables are standardized by entropy weighting method.

The content provided discusses the application of the ANN-DCC-GARCH model to Bitcoin investment trading decisions, particularly in the context of the COVID-19 pandemic. This approach involves utilizing 2019 data as out-of-sample information prior to the COVID-19 outbreak, with forecasts for this year incorporated into the training set spanning 2014 to 2018. This enriched dataset is then used to forecast the Bitcoin market situation prior to the COVID-19 outbreak. Similarly, the model considers 2022 data as out-of-sample post-COVID-19 outbreak information. Forecasts for 2022 are added to the training set covering 2014 to 2021 to predict the Bitcoin market after the pandemic. The selection of 2014 to 2021 as the training set aims to enhance the model's accuracy by increasing the data sample size, in contrast to the limited scope and potentially insufficient accuracy resulting from a 2020 to 2021 dataset. This division into pre- and post-epidemic periods, reflecting the bitcoin market's dynamics before and during the pandemic, aligns with the market's reality. Specifically, 2019's data indicates a bull market, while 2022 shows a bear market, making this segmentation meaningful for investors and valuable for testing the model's efficacy.

For instance, to comprehend the data for February 3, 2022, the DCC-GARCH model employs historical data from February 2, 2022. This data includes dynamic correlation, volatility, covariance, and other metrics as input variables for the training dataset. Additionally, a dummy variable for log returns serves as the output variable for prediction. This process is dynamic and continuously recurring, adapting to new data and market conditions.

Many researchers utilize the DCC-GARCH model to analyze the dynamic correlation and volatility of financial assets and give investment guidance by linking the conclusions of dynamic correlation and volatility. On the one side, the ANN-DCC-GARCH model supports the significant value of dynamic correlation and volatility in investment decisions. The ANN-DCC-GARCH model, on the one hand, supports the significant value of dynamic correlation and volatility in investment decisions, and on the other hand, it directly quantifies the investment and trading strategies of financial assets. Before the COVID-19 outbreak, that is, in 2019, the investment trading strategy of the ANN-DCC-GARCH model can achieve a 318% return. This clearly demonstrates that the ANN-DCC-GARCH model has a strong forecasting ability in the BTC bull market phase and can obtain excess profits. And in the bear market phase of BTC, the ANN-DCC-GARCH model can aid investors in reducing a lot of losses. Additionally, the ANN-DCC-GARCH model can establish different investment approaches for different risk preferences. We find that risk-neutral is the best choice in the bull phase of BTC, while risk-averse is the best choice in the bear phase.

The outcomes are examined in Section IV. Initially, we investigate two primary aspects. Firstly, we explore the non-symmetric long-term connection between BTC and the conventional financial assets crude Oil, Gold, and the U.S. currency. Secondly, we employ the Engle and Granger methodology to examine the long-term relationships between BTC and crude Oil, BTC and Gold, and BTC and the U.S. currency. First, the Engle-Granger cointegration test is utilized to determine that there is no cointegration between BTC and traditional financial assets. Second, there is a significant cointegration relationship between negative shocks to the US currency and positive shocks to BTC. Third, there is a cointegration relationship between positive (negative) shocks to traditional financial assets and negative shocks to BTC. Fourth, crude Oil is the Granger causality of BTC, and negative shocks to crude Oil are also the cause of negative shocks to BTC. Fifth, neither Gold nor the U.S. currency is a causal factor for BTC. These findings clarify the relationship between BTC and traditional financial assets in an asymmetric perspective, which has implications for investment decisions and risk aversion in both BTC and traditional financial assets.

In the second phase, we select the weekly information from January 2014 to April 2022, and utilize the DCC-GARCH model to assess the dynamic relationship between BTC and crude Oil, as well as BTC and Gold assets, separately. The empirical findings demonstrate that: (1) Relative to Gold and crude Oil, BTC presents higher risk, while Gold has the lowest risk. However, crude Oil exhibited an increased risk in the initial phase of the COVID-19 outbreak. (2) The BTC return is inversely associated with risk, whereas the return and risk of Gold and crude Oil do not exhibit a significant correlation. (3) The correlation between BTC and crude Oil, as well as between BTC and Gold, displays evident volatility. It is evident that the positive correlation between BTC and crude Oil notably intensified in the initial phase of the COVID-19 outbreak, while the negative correlation between BTC and Gold became more pronounced in the initial phase of the COVID-19 outbreak. These discoveries have significant added value for risk management, rational investment, emergency hedging, and more.

In the third phase, we propose an ANN-DCC-GARCH approach and utilize it to enhance investment decision-making for BTC based on historical correlation and covariance data with traditional financial assets. We split our data into two time periods: pre-COVID-19 and during COVID-19, each of which is further divided into training and prediction sets. The training set is employed to identify the most effective ANN-DCC-GARCH model in terms of prediction accuracy, while the prediction set evaluates the performance of BTC investment decisions. The empirical findings reveal that the ANN-DCC-GARCH model achieved a cumulative return of 318% in 2019 and reduced losses by 50% in 2022. Consequently, we can conclude that historical data on correlation, volatility, and covariance between BTC and traditional financial assets significantly contributes to enhancing BTC investment trading.

Additionally, the empirical findings demonstrate that the ANN-DCC-GARCH model surpasses the conventional BTC prediction model and represents the most effective machine learning model when addressing the third inquiry. Furthermore, the use of feature selection techniques did not improve the machine learning in this study. The results have implications for central banks, investors, asset management firms, and others interested in identifying reliable and accurate metrics for BTC price forecasts. This study can serve as a valuable resource for shaping asset pricing and enhancing investment decisions. It presents a significant opportunity for contribution in international finance, as the findings have important implications for asset managers' future decisions (Contribution 1).

In time series forecasting, the relationship between independent and dependent variables fluctuates over time, necessitating the re-estimation of forecasting models. Building on earlier research, this paper further examines the asymmetric cointegration and asymmetric causality of BTC and Gold, BTC and crude Oil, and BTC and the US dollar using asymmetric cointegration and causality tests. It is observed that BTC and Gold, the US dollar, and Oil elucidate the relationship between BTC and traditional financial assets from an asymmetric perspective, which is valuable for investment decisions and risk mitigation involving BTC and traditional financial assets (Contribution 2).

Additionally, the study confirms that BTC exhibits alternating positive and negative correlations with Gold, indicating that BTC can be perceived as a safe-haven asset for Gold. At the onset of the COVID-19 pandemic, BTC demonstrated a strong negative correlation with Gold, while it displayed a significant positive correlation with crude Oil. The global trade and energy demand declined in the first half of 2020 due to the COVID-19 pandemic, potentially accounting for the positive correlation between BTC and crude Oil. During this period, the price of Gold increased, leading to a negative correlation between BTC and Gold. This study, to some extent, benefits investors and financial institutions in the investment and risk management of BTC, crude Oil, and Gold (Contribution 3).

Many scholars employ the DCC-GARCH model to analyze the dynamic correlation and volatility of financial assets and provide investment advice by integrating the findings of dynamic correlation and volatility. On one hand, the ANN-DCC-GARCH model underscores the significant value of dynamic correlation and volatility in investment decisions and, on the other hand, directly quantifies the trading strategies of financial assets (Contribution 4).

It is evident from the literature in Part II that BTC has some association with traditional financial assets (Gold, Oil, and the U.S. dollar). Numerous scholars have given specific attention to the interdependence of BTC on Gold, crude Oil, and the U.S. dollar, as well as the risk premium between the two. Many scholars emphasize that determining the correlations and risk premiums of financial products is advantageous for portfolio and investment decisions. However, none of them have quantitative methods to expound on the investment decisions of financial products. Since BTC and traditional financial assets are linked in some manner, is it advantageous to make BTC investment decisions based on clarifying these relationships? This has very significant implications for most BTC investors.

According to the literature, it is demonstrated that Gold, Oil, and US dollar have strong linkage on BTC price forecasting. Therefore, we analyze the static correlation and dynamic correlation of Gold, Oil, and US dollar respectively. Meanwhile, this paper proposes a DCC-GARCH method with an artificial neural network and applies it to the investment decision of BTC. Based on the provided historical information of correlation and covariance between BTC and traditional financial assets. The analysis shows that the correlation, volatility and covariance between BTC and traditional financial assets et al. Historical information is indeed instructive for enhancing investment transactions in BTC.

This study attempts to answer the following research questions: query 1: whether is the association between BTC and two important financial assets, i.e. crude Oil and Gold? query 2: what is the association of Question 3: Which is the superior approach to predict the BTC? How does apply it to make superior investment decisions for BTC given historical information of correlation between BTC and traditional financial assets? How does apply it to make superior investment decisions for BTC given historical information of correlation and covariance with the traditional financial assets? In order to answer the first two questions, we introduced the historical data of BTC and Gold, Oil, and US dollar. Conclusion 1: The relationship between BTC and the traditional financial assets is a very important topic. BTC is chosen as the main research subject with the goal of uncovering the asymmetric integration and asymmetric causality between BTC and traditional financial assets, such as Gold, crude Oil, and U.S. dollar. The empirical findings demonstrate that there is no integrated relationship between BTC and traditional financial assets in the traditional sense, but there is an asymmetric integrated relationship. There is an integrated relationship between the rise of BTC and the fall of the US dollar index, and an integrated relationship between the fall of BTC and both the rise and fall of the three financial assets. Crude Oil is a Granger causality for BTC, Gold and the dollar are not. Before the Covid-19 outbreak, Gold's decline was the Granger causality of BTC's rise. After the Covid-19 outbreak, the fall in crude Oil prices was the Granger causation of the fall in BTC prices. The Covid-19 epidemic caused a change in the causal relationship between BTC and traditional financial assets. However, the U.S. dollar has not been a Granger causality for BTC. Finally, we discuss the practical implications of the study's findings. Conclusion 2: There is a static correlation between BTC and Gold, Oil, and the US dollar; is there a dynamic correlation row? The aim of this paper is to analyze the dynamic correlation between BTC and two important financial assets, crude Oil and Gold. This paper selects weekly data from January 2014 to April 2022, and measures the dynamic correlation between BTC and crude Oil, and BTC and Gold assets, respectively, using the DCC-GARCH model. The empirical findings demonstrate that (1) BTC is more risky compared to Gold and crude Oil, while Gold is the least risky. However, crude Oil is riskier in the early stages of the COVID-19 epidemic. (2) BTC's return is negatively correlated with risk, while Gold and crude Oil's return is not significantly correlated with risk. (3) The correlation between BTC and crude Oil, as well as between BTC and Gold, exhibit notable volatility. It can be observed that the positive correlation between BTC and crude Oil becomes considerably stronger during the initial stage of the COVID-19 pandemic. Conversely, the negative correlation between BTC and Gold intensifies at the onset of the COVID-19 outbreak. These findings have important reference value for risk prevention and control, rational investment, emergency hedge et al. In response to the fact that BTC and traditional financial assets such as the U.S. dollar, Gold, and crude Oil et al. are now increasingly favored by investors. We answer the third question by proposing a DCC-GARCH method with an artificial neutral network and applying it to the investment decision of BTC to provide historical information on the correlation and covariance of BTC and traditional financial assets. We divide the dataset into two phases based on the time series: before COVID-19 and during COVID-19, with the training and prediction sets represented in each period. The ANN-DCC-GARCH model with the best prediction error is used for the training set and to test the performance of BTC investment decisions we use the training set. The empirical findings demonstrate that the ANN-DCC-GARCH model has a cumulative return of 318% in 2019 and can reduce the loss by 50% in 2022. Therefore, we can conclude that the correlation, volatility, and covariance et al. historical information between BTC and traditional financial assets is indeed instructive for improving investment transactions in BTC. Additionally, the empirical findings demonstrate that in answering the third question, we can affirm that the ANN-DCC-

GARCH model works well for BTC investment decisions, but we are not sure how well the model predicts other financial assets. Second, according to diversification theory, investing in the BTC market alone may be risky. Therefore, the application of the ANN-DCC-GARCH model has some limitations. Therefore, our future research can explore the application of the ANN-DCC-GARCH model in diversified financial asset portfolios and further analyze the predictive effect of the model on investment transactions in other financial assets.

7.2 Implications

Cryptocurrency is one of the most rapidly growing digital currencies globally. The success of the first cryptocurrency, BTC, was marked by swift market capitalization growth, which led to the development of other forms of cryptocurrencies. Cryptocurrencies were created using blockchain technology. Contrary to traditional central authority systems, which are typically controlled by a single organization, blockchain technology adopts a decentralized approach. Due to the characteristics of BTC and its underlying technology, blockchain, governments, policymakers, investors, traders, and portfolio managers are interested in methods for market analysis and prediction. In addition, machine learning approaches have recently emerged in various fields of science and social science due to their ability to identify patterns in historical data and recognize the nonlinear relationship between variables. Therefore, this research chose to use new technologies in BTC price prediction. This chapter summarizes the current study, suggests some policies, and provides recommendations for future work.

There are some suggested policies regarding BTC that are common among authors in the existing literature, as discussed below:

Legal Definition of BTC Consumer protection should be of utmost importance to the Government, and thus the perceived illegitimacy surrounding BTC investment should be addressed. Regulations surrounding BTC should not be prepared in isolation, but in consultation with currency advocates. The District Court's opinion that BTC is a "real" currency highlights the contradiction in opinions, making it even more crucial for lawmakers to issue clear and accepted rules and regulations regarding the cryptocurrency market. There is an obvious conflict of interest involved given the intersection of the BTC market and the Government. Therefore, it is critical for the government to take a transparent position, and scrutiny should come from the Government's side as well as all involved stakeholders. It is high time for the Government to recognize and define the legality of cryptocurrencies, their users, miners, traders, exchanges, and all stakeholders. Furthermore, as miners are mainly passive and their activity is largely predictable, they should be left unregulated within the market. Apart from taxation, there is not much that needs to be regulated in that area. The rationale behind this argument is that miners are automatically rewarded for the service of mining and maintaining a public ledger. As the system is self-sustaining, further regulation by the Government is not necessary unless the mining activity is profitable in itself.

Regulation of the BTC Business Currently, even in the United States, there is uncertainty in the usage of BTC. The laws are unclear whether the current operations of the exchanges or the payment via BTC by the consumers for utilities and goods are within the scope of US legislation or not. Expectations are unclear regarding the type of records that need to be maintained and information that is to be obtained when transactions are executed in the BTC marketplace. Hence, in the spirit of the Bank Secrecy Act, it is recommended that until such time the clarification on rules, regulations, transactions, and records on BTC-related business should be maintained in detail and a confidential manner. However, on a prudent basis, all necessary details, including user identification, should be maintained.

Tackling the Illegal Market Some businesses accept BTC as a traditional medium of exchange, and for such transactions, it is suggested that the currency be treated as equivalent to Cash. However, when the transactions are made via BTC, no user's personal information is recorded to maintain anonymity, which contradicts the transactions made via a debit card or a credit card. To tackle the menace of illegal business, the Government should crack down on illicit businesses instead of consumers, which is in line with the method involved in the cash-based transaction model. To pinpoint the illegal trade or money laundering activity, the government needs to work with the BTC experts. Only a coordinated move in this regard will help to serve the purpose of both.

Adoption of Digital Currency by Central Banks In most of the markets, the government has been unreceptive of the idea. The primary reason for the same is that the technology was developed to make it autonomous and make the reliance on Government redundant. The payment and creation process will be autonomous of any specific body under the cryptocurrency mechanism. However, the very essence of this system is also the primary source of risk. The widespread use by the public might also lead to the wrongful utilization of the system by criminals. As risk mitigation, some have recommended that the Central Banks regulate the system, which can be done if the Central bank is issuing a customized cryptocurrency called Central Bank Digital Currency (CBDC). Moreover, it will be expected to have the benefits of cryptocurrency while ensuring adequate regulation, thus making the system "convenient, safe, and robust."

However, the concept is in a very early stage and is still under discussion. Whether or not a country will sustain the cryptocurrency will depend on the existing technology utilized by the country's payment system. A blockchain-enabled payment system is currently an advanced method, and the robustness of the existing system is vital for the new system to develop and be accepted by the users of that country. Unlike existing currencies, the mechanism of the CBDC is expected to be customized with its features and characteristics. Hence, the development of such a currency currently seems unlikely.

As part of diversified investment portfolios, investors are continually seeking new investment products. BTC is an intriguing new financial instrument that can enhance portfolio investment due to its high average returns and minimal correlation with financial assets. Many studies have examined the value of BTC as an investment asset, integrating it into portfolios with other major global currencies, stocks, U.S. bonds, U.S. real estate, and commodities. BTC investment provides an effective hedging mechanism for a wide range of economic sectors. Analyzing portfolio returns in further research will help educate the decision-making of investors in adding cryptocurrencies in terms of risk management and portfolio analysis.

A crucial question that remains is: What does the future hold for BTC as a diversifier and a hedging tool? This issue is quite significant for investors given the uncertain regulatory environments surrounding cryptocurrencies. While digital currencies in most nations are unregulated, researchers still explore the potential necessity of portfolio investment. Even though BTC is still in its early stages as an asset and is subject to structural changes, it is expected to remain highly volatile in the near future. Therefore, more analysis is required to minimize the risk in including BTC in portfolio investment. According to the research findings, accurate predictions of BTC prices can be profitable; hence, it can diversify a portfolio. The recommendation of this study is to use technical indicators for short-term and macroeconomic, and blockchain information indicators for long-term BTC prediction issues. Moreover, the suggestion is to use emerging machine learning models such as SVR for prediction purposes instead of traditional methods. By taking this into consideration, one can benefit from the inclusion of BTC or other cryptocurrencies in the portfolio.

7.3 Future Research

This study has some recommendations for future research, which are as follows:

This analysis was solely carried out on BTC prices. However, it would be compelling to extend the research to other cryptocurrencies such as Ethereum and Ripple. For instance, it can be evaluated whether these alternative coins exhibit similar or different results compared to BTC.

In this study, we have only utilized a limited number of attribute selection methods on the datasets. However, there are many other attribute selection techniques available, such as ranker search, Tabu search, and others, which could be further explored to improve the model.

In this report, some vital machine learning models, including SVR, Ensemble learning, and MLP, have been utilized on the datasets. In future research, additional models can be applied to the datasets.

In the current study, the impact of technical indicators has not been explored for long-term BTC price prediction. The recommendation for future research is to examine the impact of technical indicators on weekly or monthly BTC prices.

According to this study, accurate prediction of BTC prices can be profitable; thus, it can diversify a portfolio. Further research can be conducted to analyze the portfolio returns by adding BTC to a portfolio to determine the appropriate amount of BTC to hold. Based on the findings of the study, future publications can be produced.

7.4 Limitations

In this paper, draw on the relation between BTC and Gold and petrodollar, the prognosis employing a time series prognostication approach is conducted, though the precision of the prognosis is enhanced, there are still constraints in the scrutiny of multiple variables.

The prognosis model scrutinized in this paper is founded on the GRACH model, and some preliminary progress has been achieved, but due to inadequate data, brief training time, meager feature selection, and so on, the prognosis model established in this paper can be further refined, future work mainly encompasses the following points:

BTC is extremely changeable, and pursuant to Joyce Chang, head of global research at JPMorgan Chase, it is four times more volatile than Gold or stocks. The modeling in this paper does not emphasize outliers in the BTC price, which can occur for a variety of reasons, such as significant positive or negative policy announcements, necessitating the unfeasibility to disregard these outliers in the modeling. The outliers can be managed by wavelet transform, Fourier transform, and other noise reduction methods.

Despite the significance of the analysis in this paper for BTC investment, there are some constraints of this paper. Initially, we can validate that the ANN-DCC-GARCH model operates well for BTC investment decisions, but we are uncertain how well the model forecasts other financial assets. Further, according to diversification theory, investing solitary in the BTC market may entail risk. Thus, the application of the ANN-DCC-GARCH model has certain limits. In addition, in ANN-DCC-GRACH modeling, quantifiable BTC itself and indicators closely associated with BTC are selected as inputs. In actuality, there are numerous factors influencing the price of BTC, and some of these impacts, such as macroeconomic factors and government policies, are difficult to quantify, and these influences frequently have a substantial impact on the price of BTC. Concurrently, the change of BTC price is also related to investor sentiment, for these factors that are difficult to quantify in modeling, can we consider employing text mining in the domain of machine learning to extract some features, so as to refine the prognostication accuracy. With the evolution of application scenarios and technology, time series prognostication methods have progressively evolved from customary statistical methods to machine learning methods, and now deep learning is the representative method, which seeks how to realize more precise and swift time series prognostication. With the deep learning on the sequence problem of deep research, will also persist in promoting the advancement of time series prognostication technology.

With the progression of computer technology, blockchain-based technology architecture "meta-universe", "Web3", and other emerging fields are gradually entering the public's field of vision, and the digital currency represented by BTC will be regarded as an investment object by more and more people, so the use of more scientific methods to predict its price will be more and more important to the development of the time series forecasting technology. As a result, it will become the norm to utilize more scientific methods to predict the price of BTC. In future forecasting, the advantages and disadvantages of different models should be fully considered, and existing models should be synthesized and multiple deep learning models should be combined to further improve the accuracy of the prediction.

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APPENDICES

APPENDIX A

The topics in my dissertation are published as the followings:

Journal papers:

1) Liu, Y., Naktnasukanjn, N., Tamprasirt, A., & Rattanadamrongaksorn, T. (2023). Comparison of the Asymmetric Relationship between Bitcoin and Gold, Crude Oil, and the US Dollar before and after the COVID-19 Outbreak. Journal of Risk and Financial Management, 16(10), 455. (Published) (SCOPUS Q3

2) Liu, Y., Naktnasukanjn, N., Tamprasirt, A., & Rattanadamrongaksorn, T. (2024). Do crude oil, gold and the US dollar contribute to Bitcoin investment decisions? An ANN-DCC-GARCH approach. Asian Journal of Economics and Banking. (Published)

International conference papers:

1) Liu, Y., & Naktnasukanjn, N. (2022, October). Dynamic Correlation Measurement Between Bitcoin, Crude Oil and Gold. In Proceedings of the International Conference on Information Economy, Data Modeling and Cloud Computing, ICIDC 2022, 17-19 June 2022, Qingdao, China. (Published and Presentation)

Journal paper 1 (Scopus)

Comparison of the Asymmetric Relationship between Bitcoin and Gold, Crude Oil, and the U.S. Dollar before and after the COVID-19 Outbreak

Yadong Liu, Nathee Naktnasukanjn, Anukul Tamprasirt, Tanarat Rattanadamrongaksorn

The original article was published in Risk and Financial Management (Scopus Q3).

Liu, Y., Naktnasukanjn, N., Tamprasirt, A., & Rattanadamrongaksorn, T. (2023). Comparison of the Asymmetric Relationship between Bitcoin and Gold, Crude Oil, and the US Dollar before and after the COVID-19 Outbreak. Journal of Risk and Financial Management, 16(10), 455.

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Comparison of the Asymmetric Relationship between Bitcoin and Gold, Crude Oil, and the U.S. Dollar before and after the COVID-19 Outbreak

by Yadong Liu [1,2,*], Nathee Naktnasukanjn [1], Anukul Tamprasirt [1] and Tanarat Rattanadamrongaksorn [1]

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J. Risk Financial Manag. **2023**, *16*(10), 455; https://doi.org/10.3390/jrfm16100455

Received: 11 August 2023 / Revised: 15 October 2023 / Accepted: 17 October 2023 / Published: 20 October 2023

(This article belongs to the Special Issue **The Impact of COVID-19 Outbreak on Business Sustainability & Financial Risk Analysis**)

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Abstract

This paper aims to reveal the asymmetric co-integration relationship and asymmetric causality between Bitcoin and global financial assets, namely gold, crude oil and the US dollar, and make a comparison for their asymmetric relationship before and after the COVID-19 outbreak. Empirical results show that there is no linear co-integration relationship between Bitcoin and global financial assets, but there are nonlinear co-integration relationships. There is an asymmetric co-integration relationship between the rise in Bitcoin prices and the decline in the US Dollar Index (USDX), and there is a nonlinear co-integration relationship between the decline of Bitcoin and the rise and decline in the prices of the three financial assets. To be specific, there is a Granger causality between Bitcoin and crude oil, but not between Bitcoin and gold/US dollar. Before the outbreak of the COVID-19 pandemic, there was an Asymmetric Granger causality between the decline in gold prices and the rise in Bitcoin prices. After the outbreak of the

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Scopus coverage years: from 2019 to Present

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ISSN: 1911-8066 E-ISSN: 1911-8074

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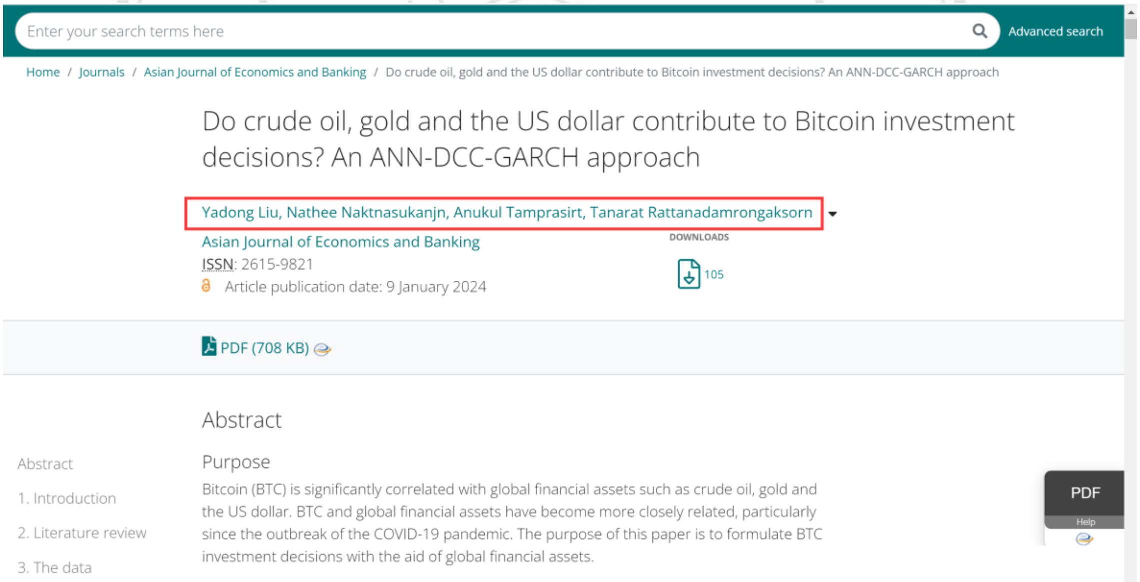
Do crude oil, gold, and the US dollar contribute to Bitcoin investment decisions? An ANN-DCC-GARCH approach

Yadong Liu, Nathee Naktnasukanjn, Anukul Tamprasirt, Tanarat Rattanadamrongaksorn

The original article was published in Journal title: Asian Journal of Economics and Banking

Liu, Y., Naktnasukanjn, N., Tamprasirt, A., & Rattanadamrongaksorn, T. (2024). Do crude oil, gold and the US dollar contribute to Bitcoin investment decisions? An ANN-DCC-GARCH approach. Asian Journal of Economics and Banking.



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Do crude oil, gold and the US dollar contribute to Bitcoin investment decisions? An ANN-DCC-GARCH approach

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Asian Journal of Economics and Banking

ISSN: 2615-9821

Article publication date: 9 January 2024

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Abstract

Abstract
1. Introduction
2. Literature review
3. The data

Purpose

Bitcoin (BTC) is significantly correlated with global financial assets such as crude oil, gold and the US dollar. BTC and global financial assets have become more closely related, particularly since the outbreak of the COVID-19 pandemic. The purpose of this paper is to formulate BTC investment decisions with the aid of global financial assets.

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International conference paper 1

Dynamic correlation measurement between bitcoin, crude Oil and Gold

Yadong Liu   Nathee Naktnasukanjn

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Proceedings of the International Conference on Information Economy, Data Modeling and Cloud Computing, ICIDC 2022, 17-19 June 2022, Qingdao, China

Research Article

Dynamic Correlation Measurement Between Bitcoin, Crude Oil and Gold

Cite BibTeX Plain Text

Yadong Liu[1], Nathee Naktnasukanjn[1,*]
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Abstract
As a financial asset, bitcoin has attracted the attention of many financial financial advisors and investors. This paper aims to analyze the dynamic correlation between bitcoin and two important financial assets, i.e., crude oil and gold. This paper selects weekly data from January 2014 to April 2022 and then uses the DCC-GARCH model to measure the dynamic correlation between bitcoin and crude oil, as well as bitcoin and gold assets. The empirical results show that: (1) Compared with gold and crude oil, bitcoin has the greatest risk, while gold has the least risk. However, crude oil proved a higher risk in the early period of the COVID-19 pandemic. (2) Bitcoin's rate of return is negatively correlated with risk, while the return and risk of gold and crude oil do not show significant correlation. (3) The correlation between bitcoin and crude oil and between bitcoin and gold shows obvious volatility. We can find that the positive correlation between bitcoin and crude oil increased significantly in the early period of the COVID-19 pandemic, while the negative correlation between bitcoin and gold became more pronounced during that time period. These findings contribute a valuable resource for choosing tools for risk prevention and control, emergency hedging, etc.

Keywords bitcoin covid-19 crude oil gold dynamic correlation

Published 2022-10-13 Publisher EAI

http://dx.doi.org/10.4108/eai.17-6-2022.2322602

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Information Economy, Data Modeling and Cloud Computing
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	Sep 2003 - Jan 2011	Instructor, Shandong Institute of Commerce and Technology

Publications

1. Liu Y. and Naktnasukanin N. (2022), 'Dynamic Correlation Measurement Between Bitcoin, Crude Oil and Gold', International Conference on Information Economy, Data Modeling and Cloud Computing, ICIDC 2022, 17-19 June 2022, Qingdao, China. https://eudl.eu/doi/10.4108/eai.17-6-2022.2322602

2. Liu Y., Naktnasukanin N., Tamprasirt A., and Rattanadamrongaksorn T. (2023), 'Comparison of the Asymmetric Relationship between Bitcoin and Gold, Crude Oil, and the U.S. Dollar before and after the COVID-19 Outbreak', Journal of Risk and Financial Management 16: 455. https://doi.org/10.3390/jrfm16100455

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