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Nerea Satrústegui Moreno

Dinámicas del mercado Bitcoin: Vencimiento de Futuros, Herding e Información

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PhD dissertation

Bitcoin Market Dynamics: Futures Expiration, Herding, and Information

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o

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ÍNDICE

Introducción

Tras su origen en 2008 como una moneda digital creada por Satoshi Nakamoto, Bitcoin se ha convertido en un tema importante y ampliamente debatido en el mundo financiero. Este activo aúna una serie de características únicas que lo hacen particular y lo distinguen del resto de divisas y activos financieros tradicionales. Algunas de las peculiaridades más destacables son: Bitcoin opera en una red descentralizada conocida como *blockchain*, que no está controlada por ninguna autoridad central como un gobierno o una institución financiera; Bitcoin puede dividirse en pequeñas partes y adquirirse fácilmente en las bolsas donde se negocia de forma continua (24/7); el activo al contado se negocia simultáneamente en muchas bolsas no reguladas formalmente, sin un modelo teórico claro que conceptualice como determinar su valor; a diferencia de los activos tradicionales, las transacciones de Bitcoin son seudónimas, lo que significa que los usuarios pueden enviar y recibir fondos sin revelar su identidad real. Aunque las transacciones se registran en la cadena de bloques pública, las identidades de las partes no se revelan.

En su origen el Bitcoin tenía un valor de cambio insignificante y solo era conocido por los inversores más especializados en mercados financieros. Sin embargo, en los últimos años, la popularidad se ha disparado, convirtiéndolo en una criptodivisa ampliamente reconocida y utilizada (Alshamsi y András, 2019). La moneda digital ha sido objeto de gran atención tanto por parte de los medios de comunicación como de los inversores, lo que refleja su creciente importancia en el panorama financiero (Urquhart, 2018). La expectación que genera el Bitcoin es muy alta para diversos grupos de interés como los inversores, los mercados financieros, los medios de comunicación, los organismos internacionales e incluso las más prestigiosas comunidades académicas. Características singulares como su escasez programada, su naturaleza descentralizada, su potencial valor como cobertura frente a activos tradicionales y la inflación, entre otras, han contribuido a hacer de Bitcoin un tema kde investigación que resulta fascinante y dinámico en el mundo de las finanzas y la tecnología.

Desde su creación, el Bitcoin ha sido objeto de numerosos estudios que han explorado una amplia gama de temas relacionados con su comportamiento y sus diversas implicaciones. El primer documento sobre esta criptomoneda lo desarrolla el propio Satoshi Nakamoto en octubre de 2008. Bajo el título *"Bitcoin: A Peer-to-Peer Electronic Cash System"* se detallan los principios básicos del Bitcoin y su funcionamiento. A partir de ese momento, surgen trabajos académicos que abordan los aspectos técnicos del Bitcoin: Jacobs (2011), Stokes (2012), Ober et al. (2013) son algunos de esos trabajos pioneros. Estos primeros estudios sentaron las bases para la posterior exploración de diversos aspectos de Bitcoin. Para el propósito de esta tesis, resultan especialmente interesantes los trabajos que desarrollan la vertiente financiera de este mercado.

De hecho, el Bitcoin ha atraído la atención de muchos investigadores en el ámbito de las finanzas debido a sus características distintivas y su impacto en los sistemas financieros tradicionales. Por ejemplo, García (2014) es uno de los primeros ejemplos de estudio del crecimiento del mercado Bitcoin, analizando la evolución desde 2010 hasta finales de 2013 con la información disponible hasta ese momento. Böhme et al. (2015) proporcionan una visión general de los principios de diseño, propiedades, usos, riesgos y cuestiones regulatorias de Bitcoin a medida que interactúa con los sistemas financieros convencionales, destacando especialmente los riesgos asociados con la integración de Bitcoin en la economía real.

Es más adelante cuando empieza a visualizarse la inquietud académica por el mecanismo de formación de precios de Bitcoin, en un intento de explicar la generación de precios desde una perspectiva más próxima al análisis fundamental. Así, Ciaian et al. (2015) empiezan a analizar la conexión entre los precios de Bitcoin, los fundamentos de la oferta y la demanda y los indicadores macroeconómicos y financieros. Ciaian et al. (2018) identifican los fundamentos del mercado, la atracción para los inversores y los indicadores financieros globales como factores clave que afectan la formación del precio de Bitcoin a corto y largo plazo. Dyhrberg (2016) sitúa a Bitcoin entre el oro y el dólar estadounidense en términos de sus ventajas como medio de intercambio y reserva de valor, enfatizando su papel en la gestión de carteras. Bariviera et al. (2017) estudió la formación de su precio a través de la existencia de ineficiencias del mercado. Sukamulja y Sikora (2018) encuentran que indicadores macroeconómicos como el promedio industrial Dow Jones, la demanda de Bitcoin y los precios del oro influyen en las fluctuaciones del precio de Bitcoin a lo largo del tiempo. Otros como Krištoufek (2015) y Andrade et al. (2021), analizaron los factores que impulsan los precios del Bitcoin, desde las fuentes fundamentales hasta las especulativas y técnicas, así como el impacto en el sector financiero. Más recientemente, autores como Li et al. (2022) e Iqbal et al. (2021) investigan la relación entre la evolución del tipo de cambio de Bitcoin y los fundamentos económicos, así como el impacto significativo de las variables del mercado de criptomonedas en la predicción de precios usando técnicas de aprendizaje automático. Srinivasan et al. (2021) demuestran cómo los indicadores macroeconómicos y la demanda influyen en las fluctuaciones del precio de Bitcoin a corto y largo plazo. Lee y Rhee (2022) proponen un modelo para examinar la relación entre los precios de Bitcoin y variables como la volatilidad del mercado de valores, los rendimientos de los bonos del tesoro, el índice de precios al consumidor y los precios del oro.

En definitiva, estos estudios enfatizan la importancia de considerar factores macroeconómicos al analizar los movimientos del precio de Bitcoin. Comprender la interacción entre los precios de Bitcoin y el análisis macroeconómico fundamental es crucial para comprender la dinámica del mercado de criptomonedas. Sin embargo, esta literatura no explica completamente la formación de precios de Bitcoin, ni su evolución a lo largo de sus años de historia. Es por ello por lo que surgen corrientes de investigación vinculadas a las finanzas del comportamiento (*behavioral finance*), con la pretensión de ofrecer una visión más completa de la realidad del mercado de Bitcoin.

Más cercanos a este ámbito Karalevicius et al. (2018) utilizan el análisis de sentimientos para prever los movimientos de precios de Bitcoin, demostrando la integración de aspectos conductuales en la predicción de precios. Hidajat (2019) revisa los sesgos de conducta en el mercado de Bitcoin, enfatizando este aspecto en la comprensión de la dinámica de este mercado. Cohen (2020) demuestra que los cambios de precio de Bitcoin no siguen la hipótesis del mercado eficiente, proporcionando perspectivas para que los inversores puedan predecir tendencias de precios. En los últimos años, autores como Guo et al. (2021), Su et al. (2022) o Jung et al. (2023), exploran técnicas de aprendizaje automático y análisis de sentimientos para predecir las tendencias de precios de Bitcoin. Otros como Arratia y López-Barrantes (2021), Zhu et al. (2021) o Gao et al. (2021) recurren a las búsquedas en Google o Twitter para continuar explorando el sentimiento y la atención que los inversores prestan a esta criptomoneda. Intentando aunar análisis fundamental y *behavioral finance*, Sun et al. (2023), por ejemplo, investigan el impacto del *hashrate* (cantidad de cálculos criptográficos que se pueden realizar en una red de criptomonedas por segundo), el volumen de transacciones, las redes sociales y las variables macroeconómicas en los precios de Bitcoin antes y durante la pandemia de COVID-19.

En conclusión, los aspectos financieros de los mercados de Bitcoin han generado un notable interés en el mundo de la investigación, tanto desde la perspectiva más tradicional del análisis fundamental como desde la visión de *behavioral finance*. Entender el comportamiento de los precios del Bitcoin ha sido uno de los temas centrales para los investigadores en finanzas, buscando identificar los factores que influyen en los cambios de precios y volumen en esta criptomoneda.

Esta tesis pretende contribuir a las líneas de investigación mencionadas, principalmente desde el punto de vista de *Behavioral Finance*, pero sin olvidar el análisis fundamental. Uno de los aspectos importantes que aúna ambos tipos de análisis es el comportamiento estacional. Desde el punto de vista del análisis fundamental, estos efectos estacionales se estudian para comprender cómo los patrones de negociación se ven influenciados por ciclos regulares y eventos predecibles relacionados, por ejemplo, con aspectos fiscales, con la publicación de indicadores económicos o con procedimientos técnicos propios de los mercados que, en buena lógica racional, afectan a la liquidez, la volatilidad y el flujo de órdenes. Pero, por otro lado, las emociones, sentimientos y sesgos cognitivos de los inversores pueden llevar a decisiones de compra o venta en momentos específicos (periódicos o no) que no necesariamente se alinean con las expectativas del mercado basadas en fundamentales. Esta vertiente conductual es especialmente relevante en el mercado de Bitcoin, donde se pone de manifiesto una elevada volatilidad, precisamente por la dificultad de valorar esta criptomoneda usando variables fundamentales.

Así pues, uno de los objetivos de la tesis es analizar patrones de estacionalidad en el mercado de Bitcoin, ya que estos patrones pueden proporcionar información valiosa sobre el comportamiento de los precios de la criptodivisa y su volumen en diferentes marcos temporales. Detectar si existe estacionalidad, no solo ayuda a los inversores a tomar decisiones informadas con respecto al momento de sus operaciones y estrategias de inversión, sino que también les permite anticipar tendencias y ajustar sus estrategias en consecuencia, lo que resulta fundamental en un entorno financiero dinámico y complejo. Al reconocer las fluctuaciones estacionales, los participantes del mercado pueden adaptar sus estrategias de negociación para aprovechar las oportunidades o mitigar los riesgos asociados con estas variaciones (Fraz et al., 2019 y Aslanidis et al., 2020). En particular, y por la relevancia que tuvo para el mercado de Bitcoin la creación del correspondiente mercado de futuros (Jalan et al., 2021, Kim et al., 2020, Baur y Dimpfl, 2019), nos centraremos en el estudio de la posible estacionalidad que supone el vencimiento de los futuros sobre Bitcoin. De hecho, autores como Nekhili (2020) y Yang, (2022) encuentran que los futuros de Bitcoin mejoran la eficiencia en la formación de precios de las criptomonedas y mejoran la estabilidad y la efectividad de la información del mercado de Bitcoin, reduciendo las barreras a la inversión.

En esta misma línea de investigación sobre la estacionalidad del vencimiento de los futuros, consideramos interesante analizar la presencia de uno de los fenómenos más notorios de *Behavioral Finance*: el comportamiento gregario (efecto *herding*), donde los inversores imitan las acciones de otros en lugar de basarse en su propia información. El efecto *herding* ha sido identificado como un factor clave en la irracionalidad colectiva de los inversores (Bikhchandani y Sharma (2001), o Hirshleifer y Teoh (2003), son algunos de los autores determinantes de esta consideración). Los estudios han examinado extensivamente el impacto del sesgo de manada en la toma de decisiones de inversión, mostrando que tanto la sobreconfianza como el comportamiento gregario tienen una influencia sustancial en dichas decisiones (Madaan y Singh, 2019). Pero este comportamiento no se limita solo a los inversores individuales, sino que también se extiende a los inversores institucionales (Tse y Tucker, 2009), que son agentes claramente protagonistas en los momentos de vencimiento de los instrumentos derivados. Por esta razón consideramos que el estudio del efecto *herding* en momentos de evidente estacionalidad como son los vencimientos de futuros sobre Bitcoin puede aportar evidencia de la importancia de los sesgos emocionales y cognitivos en el mercado de criptomonedas y, especialmente, de la relevancia del ámbito de *Behavioral Finance* en la formación de precios de Bitcoin.

No obstante, esta tesis no quiere renunciar a la investigación más tradicional sobre la incorporación en los precios de la información disponible, idea clave en la conceptualización de la eficiencia del mercado. Las noticias y eventos en los medios pueden influir significativamente, no solo en los patrones estacionales, sino de manera continuada al generar cambios en la percepción del mercado, la confianza de los inversores y las expectativas económicas. Es crucial valorar cómo las noticias y la información en los medios pueden afectar el comportamiento del mercado, romper o crear tendencias y generar oportunidades o riesgos para los inversores y participantes del mercado del Bitcoin (Gbadebo, 2023 y Sun et al., 2023). Al examinar el impacto de los diferentes tipos de información sobre los precios de Bitcoin, los investigadores pueden mejorar los modelos predictivos, mejorar la eficiencia del mercado y profundizar en la comprensión de los mecanismos que subyacen en los cambios de precios.

En este contexto se desarrolla esta tesis. La principal motivación de los estudios presentados es contribuir a la literatura existente proporcionando un mayor entendimiento sobre la formación del precio del Bitcoin al tiempo que se exploran diversos factores que podrían estar influyendo en dicho proceso. En concreto, hemos identificado y evaluado la influencia de los denominados “efecto vencimiento” y “efecto *herding* en el vencimiento” en el mercado de Bitcoin, a la vez que examinamos el impacto que tienen noticias relevantes en el precio y el volumen de esta criptomoneda. Al hacerlo, esperamos enriquecer el debate académico y proporcionar perspectivas útiles para inversores, reguladores y otros actores interesados en comprender y participar en el mercado del Bitcoin.

El desarrollo tiene la siguiente secuencia:

En el primer capítulo denominado: *Is there an expiration effect in the Bitcoin Market?* hemos analizado el efecto vencimiento de los futuros en el mercado de Bitcoin. Por definición, el efecto vencimiento se refiere al impacto sobre la cotización (precio), la volatilidad y el volumen en el mercado de contado en torno al vencimiento de los contratos de derivados. El efecto de vencimiento puede afectar a los precios de los activos financieros y a la liquidez en el mercado de contado, ya que los participantes en el mercado ajustan sus posiciones en torno al vencimiento de los contratos de opciones y futuros.

Este impacto ha sido ampliamente estudiado en los mercados tradicionales permitiendo encontrar consecuencias relevantes en diversas medidas de negociación. El primer estudio sobre el efecto vencimiento se remonta a 1974 (Nathan, 1974). Después, muchos otros investigadores han aportado a la literatura con sus hallazgos detectando aumentos de volumen y volatilidad (Stoll y Whaley (1997), Gurgul y Suliga (2019), Dewan y Dharni, (2019) o Singh y Shaik (2020) entre otros).

En el caso del Bitcoin, no fue hasta 2017 cuando se negoció por primera vez un contrato de futuros en un mercado regulado. Concretamente en diciembre de 2017, CME y CBOE empezaron a negociar futuros del Bitcoin. Esto hecho supuso un paso adelante para esta criptomoneda y consideramos que la llegada de la negociación de futuros es una ocasión ideal para analizar este efecto con consecuencias tan relevantes en un mercado con características tan singulares.

Para realizar este primer capítulo hemos tenido en cuenta las siguientes premisas: Dada la fragmentación del mercado spot de Bitcoin, hemos analizado el efecto vencimiento en siete bolsas de Bitcoin relevantes (Bitstamp, Coinbase, Itbit, Kraken, Gemini, Binance y Bitfinex), con un volumen de negociación significativo, pero con diferencias entre ellas. Para el vencimiento de los futuros, hemos analizado los tres mercados regulados (CBOE, CME y BAKKT) que pueden ser útiles para ofrecer resultados sólidos.

Las conclusiones son claras; hemos detectado efecto vencimiento en el mercado de Bitcoin, lo que significa que encontramos cambios significativos en volumen, rentabilidad y volatilidad en el periodo justo anterior, durante y / o posterior al momento de vencimiento de contratos de futuros. En particular, consideramos posible que sean los inversores institucionales los que refuerzan la existencia del efecto vencimiento, dado que su mayor grado de sofisticación respecto a los inversores minoristas puede brindar mayores oportunidades de arbitraje y/o especulación en momentos cercanos al vencimiento. Específicamente, estos efectos son más pronunciados a medida que nos acercamos al vencimiento de los futuros, con una reducción notable en el volumen y la volatilidad después del momento vencimiento. Al analizar las fechas de vencimiento mensuales en los tres mercados regulados, observamos que los efectos no son uniformes. Mientras que los vencimientos CME y CBOE muestran aumentos similares en volumen y volatilidad antes del vencimiento, y disminuyen sustancialmente después, los vencimientos Bakkt muestran efectos negativos antes del vencimiento y una dirección común con CME y CBOE después del vencimiento. En el mercado de CME se observan los efectos más significativos. Esto puede atribuirse no solo al mayor volumen de negociación en este mercado, sino también a que el CME es el mercado con la serie temporal más larga. Antes de la fecha de vencimiento, especialmente para los contratos liquidados en efectivo, se observa un aumento en el volumen de negociación, que luego disminuye. La volatilidad sigue un patrón similar, aunque más concentrado. En cuanto a los rendimientos, no se detecta un patrón consistente; el único efecto claro del vencimiento está relacionado con la hora específica de vencimiento en el CME.

Así pues, empíricamente confirmamos una clara anomalía en el mercado al contado coincidiendo con las fechas de vencimiento de los futuros, un fenómeno que se manifiesta notablemente en las horas cercanas al vencimiento. Sin embargo, la compleja interacción de numerosos factores que influyen en este efecto impide identificar con precisión sus causas.

El capítulo se recoge en el artículo "*Is there an expiration effect in the Bitocin Market?"* que ha sido publicado en la revista *Review of Economics and Finance* en 2023.

Tras confirmar en el primer estudio que existe efecto vencimiento en el mercado de Bitcoin, el segundo capítulo denominado "*The witching week of herding on Bitcoin exchanges*" trata de seguir enriqueciendo la literatura analizando el efecto *herding* (también denominado efecto manada o comportamiento gregario) entre las bolsas de Bitcoin en un momento muy concreto: en torno al vencimiento de los futuros del Bitcoin negociados en el CME.

Por definición, el efecto *herding* se refiere al fenómeno en el que los individuos tienden a imitar las acciones de otros en lugar de tomar decisiones basadas en sus propias creencias o información (Hidayati et al., 2022). Este comportamiento se observa a menudo en los mercados financieros, donde los inversores pueden seguir las acciones de otros sin tener necesariamente una intención unificada (Babar et al., 2016). En un contexto de racionalidad limitada, cuando la información privada de los individuos se ve desbordada por la influencia de la información pública, muchos inversores pueden tender a seguir el consenso del mercado (Denenow y Welch, 1996; Bikhchandani y Sharma, 2001; Hirsfleifer y Teoh, 2003, entre otros, argumentan en esta línea).

Este fenómeno ha sido objeto de amplia investigación en los mercados financieros convencionales, proporcionando una comprensión más profunda del comportamiento de los inversores y las implicaciones que conlleva. La identificación del efecto *herding* en los mercados es crucial debido a sus múltiples consecuencias para las bolsas: puede incrementar la volatilidad en el mercado, es posible encontrar ineficiencias en la fijación de precios e incluso pueden producirse burbujas bursátiles (Wang et al., 2018).

Teniendo en cuenta los aspectos relevantes que tiene el efecto *herding* en los mercados, desde el auge de las criptomonedas se ha abierto un nuevo campo de estudio en un entorno diferente por el nuevo marco formativo que ofrecen estos activos. Analizar e identificar el efecto *herding* y sus consecuencias en las criptodivisas es un tema de gran interés ya que ofrece valiosas perspectivas sobre los procesos de la toma de decisiones de los inversores. Por este motivo, en los últimos años se han realizado relevantes investigaciones que analizan el efecto manada en los mercados de las criptodivisas, especialmente en el periodo de pandemia (Yarovaya et al. (2021), Demir et al. (2020), Caferra et al. (2021), Kumar (2020), o Gamma Silva et al. (2019), entre otros).

Sin embargo, aunque otros investigadores han tratado de detectar el "efecto *herding*" en las criptodivisas, consideramos que nuestro estudio aporta un doble valor añadido a la literatura ya que ninguno de los estudios se ha centrado en estudiar el denominado efecto *herding* entre las bolsas de negociación de referencia de Bitcoin (aunque Blasco y Corredor (2022) estudian dicho efecto entre diversas bolsas sin diferenciar en destacables y no) y, adicionalmente, es el único trabajo que estudia el efecto gregario en torno al vencimiento de los contratos de futuros.

Así, para llevar a cabo la investigación, al igual que para nuestro primer análisis, en los precios al contado de Bitcoin hemos seleccionado siete bolsas de referencia que suelen estar entre el 10% de las principales bolsas del Bitcoin: Bitstamp, Coinbase, itBit, Kraken, Gemini, Binance y Bitfinex. Hemos empleado datos intradiarios, los cuales añaden un valor significativo y una mayor robustez a nuestra investigación.

Nuestro estudio confirma, en promedio, la presencia de un comportamiento *anti-herding* durante el periodo analizado. No obstante, nuestros hallazgos revelan una dinámica más compleja al mostrar que en momentos específicos, caracterizados por la saturación de información, puede surgir el *herding* si los inversores encuentran dificultades a la hora de procesar la información. Concretamente, estos efectos se extienden a lo largo de la semana anterior al vencimiento y desaparecen rápidamente el día siguiente al vencimiento.

Específicamente, los resultados indican que, en general, los precios del Bitcoin tienden a reflejar la información de los inversores. Sin embargo, este punto no es tan claro durante la semana de vencimiento de los futuros de Bitcoin, ya que parece que los inversores se monitorean estrechamente entre sí. Si el efecto *herding* se manifiesta claramente durante la semana de vencimiento, el flujo de información podría volverse menos preciso y estar distorsionado. En períodos de vencimiento, los inversores se enfrentan a una diversidad de información que influye en sus decisiones de inversión. Por este motivo, muchos inversores desinformados pueden encontrar útil imitar las decisiones de otros, trasladando esa imitación a las distintas bolsas en las que se negocia el Bitcoin. La práctica del *herding* entre diferentes bolsas puede llevar a una amplificación de los precios del Bitcoin que no refleja su valor intrínseco, ya que las decisiones basadas en la imitación pueden distorsionar los movimientos de precios.

Como resultado, los inversores y otros agentes del mercado se enfrentan a un aumento del riesgo asociado con una mayor volatilidad y la posibilidad de encontrarse con precios erróneos. Esta situación puede tener implicaciones significativas para la gestión de riesgos y la toma de decisiones estratégicas en el contexto de inversiones en Bitcoin y otros activos financieros.

Este capítulo da origen al artículo "*The witching week of herding on Bitcoin exchanges*" que fue publicado en la revista internacional *Financial Innovation* en 2022.

Continuando con nuestro objetivo de abordar los factores que influyen en la formación de los precios de los activos, hemos desarrollado el último capítulo de la tesis denominado *"Some of the ingredients spicing up the bitcoin price: Covid, inflation and war"*, el cual se centra en analizar el impacto de la publicación de noticias en los medios de comunicación en la cotización del Bitcoin.

En principio, en mercados eficientes las cotizaciones deben reflejar toda la información que existe en el mercado en cada momento. Comprender cómo las noticias influyen en la cotización de los activos es importante ya que puede ayudar a los inversores a anticiparse a los movimientos de los mercados, descubrir tendencias e incluso identificar oportunidades de inversión.

Sin embargo, desde los primeros trabajos de Ederington y Lee (1993, 1995), y a pesar de la relevancia del tema, no son tantos los autores que investigan el efecto de la cobertura mediática en los rendimientos y el volumen de los activos financieros. No obstante, trabajos como los de Blasco et al. (2002) o Ahern y Sosyura (2014), enfatizan la influencia de las noticias en la dinámica del mercado financiero.

Basándonos en esta literatura, podemos vislumbrar que la información publicada por los medios de comunicación puede influir significativamente en los precios de mercado al moldear, a su vez, el sentimiento de los inversores. Así lo demuestran estudios como los de Chen et al. (2013), Yu (2022) o Ambros et al. (202), afirmando que la información ofrecida en los medios de comunicación puede alejar significativamente los precios de cotización de sus valores fundamentales resaltando, nuevamente, la interrelación existente entre el análisis fundamental y las finanzas del comportamiento.

En el caso concreto del Bitcoin, también se ha tratado de demostrar la influencia que tienen las publicaciones en los medios de comunicación en los cambios de precios, volatilidad y volumen del Bitcoin. Por ejemplo, Karalevicius et al. (2018), Zaman et al. (2022) y Béjaoui et al. (2021), han identificado una interacción entre el sentimiento de los medios de comunicación y los precios de Bitcoin, lo que indica que los inversores tienden a reaccionar rápidamente a las noticias, lo que puede dar lugar a reacciones exageradas a corto plazo. Además, el sentimiento y la cobertura de los medios de comunicación pueden influir en los precios del Bitcoin durante acontecimientos significativos como la pandemia COVID-19 (Gherghina y Simionescu (2023). Otros investigadores como Sun et al. (2023) destacaron la importancia del sentimiento de las redes sociales a la hora de predecir las valoraciones de Bitcoin, indicando que las diferentes plataformas de redes sociales pueden tener diferentes impactos en los precios de Bitcoin. Además, el estudio de Gao et al. (2021) reveló que el sentimiento financiero de Twitter puede afectar significativamente a los rendimientos y la volatilidad de Bitcoin, lo que sugiere que el análisis del sentimiento de los medios sociales puede proporcionar información sobre los movimientos de precios de Bitcoin.

En este contexto se lleva a cabo el estudio. Para poder realizar nuestro análisis es preciso acotar el horizonte temporal para tratar adecuadamente la información. Se selecciona el periodo entre mayo de 2018 y noviembre de 2023 ya que es un periodo de tiempo en el que han confluido importantes acontecimientos globales. Por un lado, la pandemia del Covid-19 que ubicó a las economías en una situación de alerta sanitaria sin precedentes. Las consecuencias de la pandemia desencadenaron un elevadísimo repunte de inflación que hizo que los bancos centrales tuvieran que actuar para proteger a las economías. Adicionalmente, el estallido de la guerra entre Ucrania y Rusia, incorporaba mayor inestabilidad al mercado.

Teniendo en cuenta que éstas han sido las grandes preocupaciones durante el periodo analizado (Covid, inflación y guerra), se ha analizado el impacto que tienen noticias relacionadas con esas temáticas en la cotización del precio del Bitcoin.

Para desarrollar el trabajo, se han realizado los siguientes pasos: en primer lugar, construimos una base de datos con las noticias relevantes de los temas que queríamos analizar (Covid, inflación y guerra), utilizando la base de noticias de Proquest ya que permite la selección de la información a partir de términos específicos. En segundo lugar, identificamos los días con mayor acumulación de noticias para cada uno de los temas a analizar. Posteriormente, seleccionamos los 100 días con información más significativa sobre cada uno de los temas (Covid, inflación y guerra). Posteriormente, utilizamos la base de noticias proporcionada por Bloomberg, para extraer la información de los días seleccionados. Este punto es de gran valor, ya que Bloomberg proporciona información detallada sobre la hora de publicación de la noticia (horas, minutos y segundos).

Con esta información, continuamos nuestro estudio en dos etapas. En la primera examinamos el patrón de precios con una frecuencia intradiaria por hora, que hemos denominado como “visión de media distancia” y en la segunda fase, hemos examinado el comportamiento de los precios con mayor profundidad, utilizando los datos segundo a segundo, lo que podemos denominar como “visión a corta distancia”.

Nuestros resultados con información hora a hora nos indican que las noticias de Covid y guerra se anticipan en los mercados, provocando grandes fluctuaciones de precios. Para la inflación, el impacto se concentra en el momento de la publicación. Sin embargo, en el análisis realizado con los datos segundo a segundo se observa que las noticias sobre Covid o guerra tardan hasta dos horas en procesarse tras su publicación, mientras que las noticias programadas con una fecha concreta, como la publicación de la inflación, tienen menos impacto en el tiempo.

Nuestro estudio ha destacado la complejidad de determinar el impacto preciso de una noticia cuando existe información relacionada que puede crear expectativas sobre noticias futuras. Además, cuando la reacción a una noticia se ve influenciada por la publicación casi simultánea de otra, puede resultar desafiante separar los efectos individuales de cada una. Por lo tanto, es crucial considerar cuidadosamente la frecuencia temporal de los datos utilizados en el análisis para evitar distorsionar los efectos reales de una secuencia de noticias debido a su proximidad temporal o para evitar enmascarar la influencia de una noticia con otros efectos.

Este capítulo se recoge en el artículo *“Some of the ingredients spicing up the bitcoin price: Covid, inflation and war”* que ha sido recientemente enviado para su valoración a una revista indexada como Q1 en JCR.

Con todo ello, consideramos que la tesis propuesta enriquece a la comunidad académica, representando un avance significativo en el campo de la investigación. Nuestros hallazgos proporcionan valiosas perspectivas que pueden ayudar a los inversores y profesionales en la toma de decisiones, así como ser utilizados por los reguladores del mercado en el actual desafío de adaptar los marcos regulatorios existentes para abordar los riesgos asociados al Bitcoin.

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PART 1: Is there an expiration effect in the Bitcoin market?

Is there an expiration effect in the Bitcoin market?

Abstract

This paper studies the monthly expiration effect in the bitcoin markets. The emergence of trading in bitcoin futures in regulated markets is an ideal occasion to test this effect on an asset with singular characteristics. Our results with intraday data show that around the time of maturity there are significant changes in the trading volume, volatility and return of bitcoin, an asset that is traded in many exchanges simultaneously. Therefore, there is a clear expiration effect related to bitcoin futures. The closer to the expiration time (shortly beforehand or afterwards), the more intense these effects are. However, in spite of these general results, the expiration effect is not homogeneous across exchanges and depends on the characteristics of the futures contract in question. Robustness tests are also applied to confirm the results. The increasing participation of institutional investors is consistent with our findings, particularly in relation to the expiration effects of cash-settled futures, as these contracts are more appealing for sophisticated investors who could be interested in arbitrage or speculative processes.

1. Introduction

Since the 1980s, after the definitive setting up of the derivatives market and the emergence of the first studies detecting the expiration effect, there has been extensive financial literature analysing this alleged anomaly. The expiration effect is defined as the spot market anomalies detected shortly before or after the maturity date of the related derivatives. The explanations traditionally proposed for such effect are based on the different types of investors´ behaviour, the characteristics of the settlement systems or the variety of underlying assets and derivative contracts, among others.

The irruption of crypto-currencies in the economy and the development of regulated bitcoin futures markets offer a challenging opportunity to further advance the understanding of this phenomenon. In December 2017, CME and CBOE started to trade futures on bitcoin with the particularity that the underlying asset was not traded in a formally regulated market, as it is usually understood. This situation provides an incentive to test our objective, which is to analyse whether bitcoin trading volume, volatility and return behave differently on the expiration date of bitcoin futures as compared to non-expiration times.

This study contributes to the empirical literature in several ways. It is the first paper, as far as we know, that analyses this anomaly in the bitcoin market. Bitcoin has singular features that make its study particularly attractive. It does not rely on central banks or any other institution regulating money supply or serving as an intermediary, it enables almost anonymous transactions, which are irreversible, and it can even be divided into small parts and can be purchased easily on appropriate 24/7 exchanges that allow traditional currencies to be exchanged for bitcoins and vice versa. Moreover, spot bitcoin is traded in many non-formally regulated exchanges simultaneously, without a clear theoretical model conceptualizing how to determine its value. These characteristics distinguish bitcoin from other assets previously studied in the literature of the expiration effect, and therefore its study may offer valuable additions to existing knowledge. Secondly, given the fragmentation of the bitcoin spot market, we study the expiration effect on seven significant but very different individual markets. This analysis allows us to observe possible differences among spot markets according to their different running procedures and characteristics. Thirdly, we study the expiration of bitcoin futures traded on three representative and popular regulated markets offering different contract specifications, settlement systems and expiration dates, which can help to understand the reasons behind the maturity effect. Fourthly, we use intraday data. Since in both spot bitcoin exchanges and regulated bitcoin futures markets several features converge that can drive the effect in opposite directions, the use of daily data can mask the results. Intraday data allow a more in-depth analysis round about the precise time of expiration. Fifthly, depending on the results obtained, we could try to infer the behaviour of the different groups of investors who negotiate in these markets. Finally, the work gives some pointers for market supervisors and regulators. If anomalies do not reflect new information in the market, regulators should seek ways to mitigate them so that markets will work more efficiently. Identifying whether such an anomaly occurs is the first step in that process.

The remainder of the paper is structured as follows. The second section provides the literature review, the third section describes the database, the fourth section shows the methodology and the results, and the fifth and final section sets out the discussion and the main conclusions of the paper.

2. The expiration effect: literature review

2.1. Previous empirical literature

The expiration effect is an anomaly observed in prices, trading volume and volatility around the expiration date of a derivatives contract. The first study to analyze the expiration effect dates back to 1974 when the Nathan Report examined it and did not find any abnormal behavior. As pioneering works, we mention Klemkosky (1978), Cinar and Vu (1987) or Vu and Cinar (1988) that find negative returns in the dates previous to the expiration, reverting to positive returns after that date. Stoll and Whaley (1987 and 1991) also analyze the behavior of trading volume and volatility and observe increases on the maturity date. Pope and Yadav (1992) find increases in trading volume but not in volatility. There are also some papers that analyze the joint expiration of several derivative assets, which is known as the “witching hour”. Chamberlain, Cheung and Kwan (1989) or Chen and Williams (1994) analyze this phenomenon without finding conclusive results. Alkebäck and Hagelin (2004) summarize the main initial works describing the market under study, the corresponding underlying asset and the results obtained.

Following this pioneering research, the literature on the expiration effect is extensive, analyzing the American markets as well as other markets worldwide. The analyses focus on the behavior of the three usual variables (trading volume, volatility and price), but the results are not unanimous due to the differences among assets, markets and periods analyzed as well as the techniques applied. Some examples are the papers by Bollen and Whaley (1999), Chow, Yung, and Zhang (2003), Chung and Hseu (2008), Corredor, Lechon and Santamaria (2001), Karolyi (1996), Lien and Yang (2003 and 2005) and Vipul (2005), among others. More recently, Xu (2014) studied this effect around the quadruple witching Friday, and Batrinca, Hesse and Treleaven (2020) extended the analysis of the effect to the Pan-European equity markets.

The reasons for the expiration effect can be primarily found in the fact that, in the derivatives markets, speculators, hedgers and arbitrageurs trade together. Their actions can affect the information flow due to arbitrage, speculative and manipulative processes between the spot and the derivatives markets. These strategies might play a relevant role on the maturity date. However, the existence of transaction costs gives some market participants an advantage over others. Investors may act differently, even neutralizing each other´s actions. This means that, a priori, the aggregate observable effect is not obvious.

Stoll and Whaley (1987) suggest that arbitrageurs in the stock market, who can incur the lowest transaction costs, may unwind their spot positions in the same direction when the expiration date arrives. If this unwinding is not anticipated, temporary mismatches between buy and sell orders can occur, putting pressure on the price of the underlying asset and leading to unusually large price swings which will potentially reverse on the following day. Fung and Yung (2009) indicate that the settlement procedure affects the unwinding of spot-futures arbitrage positions. For example, if the settlement value is obtained with an average price calculated at five-minute intervals, arbitrageurs will focus on buying or selling the spot around the five-minute time marks.

Speculators may also find the expiration time to be the ideal moment to develop strategies to act on prices, assuming the existence of agents who may occasionally alter prices (Klemkosky, 1978). These investors have uncovered positions and try to influence the price by buying or selling the underlying asset in the spot market around the key times to settle the derivatives contract at a price favorable to their position (Fung & Yung, 2009).

On the expiration date, there is also the possibility of establishing profitable manipulation strategies (Kumar & Seppi, 1992). For example, “capping” strategies and the opposite practice, “pegging”, manipulate prices by selling (buying) large amounts of a commodity or security close to the expiration date of its options to prevent a rise (decline) in the underlying´s price (Pope & Yadav, 1992). Other practices such as option pinning, which is the tendency of stock prices to run close to the strike price of heavily traded options on the days of expiration, or investors’ preference for stock price clustering in round numbers, may also force stock prices to deviate from their fair value (Ni, Pearson & Poteshman, 2005). Although these practices are found in the option markets, they can also affect related markets such as the futures markets (Golez & Jackwerth, 2012) when market makers rebalance their delta hedging near maturity.

These practices can be reflected in the trading volume. If arbitrageurs, speculators and manipulators use the expiration date to trade more intensively, an abnormal volume will be observed. Since trading volume is closely related to volatility, significant movements in volume can consistently result in noticeable volatility changes. Both variables convey the information flow available in the markets. Their variations will depend on investors´ behaviour that, in turn, will also generate new information flows.

Lien and Tse (2006) show in an exhaustive review that the manner of delivery, physical or cash, can cause the expiration effect, and Xu (2014) summarizes different settlement procedures in worldwide markets that could affect the identification of the anomaly. Chay, Kim and Ryu (2013) describe different procedures established worldwide to determine the settlement price of index derivatives in order to try to minimize the maturity effect. They find that the expected settlement price calculated continuously during a final 10-minute call auction and immediately disclosed mitigates the effect. However, there is no clear evidence that a call auction procedure during a period is systematically effective in decreasing the maturity effect (Chay & Ryu, 2006). Other changes in the settlement systems did not have more successful results. Switching from taking the closing price to taking the opening price moves the effect to the next day, but does not remove it (Stoll & Whaley, 1991). Other authors such as Chow, Yung and Zhang (2003) suggest that using the average price over a specific period rather than the price at a specific time mitigates the effect. If the pricing period is longer, arbitrageurs are expected to extend their operations for a longer time to ensure their arbitrage profits. Despite the inconclusive results, authors such as Agarwalla and Pandey (2013) emphasize the importance of the settlement procedure in the expiration effect in more traditional financial markets.

2.2. Bitcoin Futures

In traditional markets, the introduction of derivatives complements the spot market and creates new opportunities for risk transfer. Traders can negotiate in the spot and/or in the derivative markets and the information will be visible in the market chosen for trading in the first instance and can subsequently affect transactions made in the other market. The introduction of regulated bitcoin futures has increased bitcoin´s popularity and allows increasing the range of assets to trade and cover the risk, bringing in new participants in a market hitherto dominated by retail investors. The existence of these derivatives is expected to gain the attention of institutional investors, which will increase market liquidity. Traders can take advantage of the bitcoin movements without the need of trading on the spot. Furthermore, regulated bitcoin futures enable traders to trade in jurisdictions that have prohibited crypto-assets.

Should we expect an expiration effect in the bitcoin market? As outlined above, bitcoin markets have some characteristics that can affect market variables in opposite directions and with different intensity. The final effect will depend on the aggregated result. Therefore, the identification of the expiration effect is an empirical question. In fact, if an expiration effect is detected, the results can help to identify those bitcoin market characteristics playing a major role in it.

On the one hand, it is worth noting that bitcoin futures markets, being of recent creation, still have relatively very small trading volumes despite the attractiveness for institutional investors. Perhaps lower than usual liquidity levels, wide spreads or fear of trading halts mechanisms in response to high volatility are the causes of their still limited participation. If the futures trading volume is low, we should not expect any effect on spot bitcoin prices at futures maturity.

On the other hand, bitcoin spot markets are relatively small too, illiquid and not very deep (compared to traditional markets). In this scenario, any strategy carried out by arbitrageurs and speculators may have a greater impact on prices. The small size can also make the spot market more susceptible to manipulation. Furthermore, the bitcoin spot market is a fragmented market. This means that strategies can be carried out in several exchanges. If there were lead-lag effects or temporal price discrepancies between exchanges, arbitrage operations would be easier to implement for those traders who incur low transaction costs. In addition, speculators and price manipulators can operate by buying or selling in those exchanges that are more attractive from the point of view of achieving their objectives. Accordingly, a significant expiration effect is to be expected if arbitrageurs, speculators or price manipulators decide to intervene.

The settlement system also requires consideration for its possible involvement in the expiration effect. Futures markets such as CME and CBOE follow a cash settlement system that, a priori, would affect the spot prices to a minor degree since the delivery of the underlying asset is not necessary. Although sharing this common pattern, the reference rate for settlement in CME is based on bitcoin prices traded in several exchanges whereas CBOE takes an auction-based settlement price from only one exchange. However, according to the previous literature, cash settlement would lead to a small effect when the maturity date is due. In turn, other markets such as the Bakkt platform supervised by Intercontinental Exchange (ICE) follow a settlement system by physical delivery and do not require pricing data from the spot market. If differences in the settlement system were to lead to a significant effect on the spot market at maturity, it would be observed differently in those spot exchanges involved in each settlement system.

It should also be taken into account that some significant exchanges such as Binance, Bitfinex and Kraken also trade bitcoin futures, although not regulated by traditional institutions, as is the case of CME, CBOE or ICE. These futures contracts may have different specifications but some expiration dates may coincide with those offered by, for example, CME. In these cases, if any expiration effect were detected, it would not be possible to determine the magnitude of the expiration effect attributable to each contract. Nevertheless, this coincidence is unimportant given that the largest share by far of derivatives futures traded in unregulated markets are perpetual futures (De Blasis and Webb, 2022) which do not have a specific maturity date and, therefore, cannot originate an expiration effect.

Finally, it is worth remembering that institutional investors´ trading can play a decisive role in the period around expiration dates, since they are more sophisticated investors that can take advantage of some of the difficulties individual investors face to find profit opportunities. As institutional investors´ participation increases, the possibility of finding an expiration effect increases too.

3. Database

This paper focuses on the monthly expiration effect on seven popular bitcoin exchanges that represent a significant trading volume but also exhibit some differences in characteristics that can be helpful for finding robust results. Five of these are constituent exchanges providing pricing data to calculate reference rates and spot price indexes of the underlying asset in some futures contracts: Bitstamp, Coinbase, Itbit, Kraken and Gemini. We also include two other bitcoin reference markets in the analysis: Binance and Bitfinex. Binance is usually considered the biggest cryptocurrency market by volume, but all seven are in the top 10% of bitcoin exchanges. All are centralized exchanges, private companies offering trading platforms that require their clients´ registration and identification, providing higher volume and liquidity than decentralized exchanges (direct peer-to-peer transactions, without intermediation) and attracting professional and institutional investors.

We use daily and intraday data provided by CryptoDataDownload. Intraday data constitute the base of our analysis whereas daily data are used for descriptive purposes and in robustness tests. Intraday data are hourly records and contain open, close, high and low prices of the period and trading volume in BTC. The total period covers the beginning of the futures contracts in December 2017 (we take December 31, 2017 as the initial date) until November 20, 2020. The total number of observations is 25,305 for each variable and exchange.

For bitcoin futures, we have considered three regulated alternative markets for monthly expiration dates. Regulated futures present some advantages over unregulated futures for our analysis. On the one hand, having robust traditional security measures (e.g. rulebooks that clearly define how they handle possible defaults without mutualizing losses), the regulated markets attract institutional investors, who are supposed to make educated and informed decisions and contribute to market efficiency. On the other hand, some transparency issues related to faked volume reported by unregulated markets (Cong et al., 2021) lead us to opt for regulated markets to obtain the most accurate possible results.

Although CBOE was the first market to trade futures on bitcoin on 10th December, the contracts offered by the CME on 17th December, one week later, triggered the trading in futures. CME futures trading is currently active, but CBOE released its last bitcoin futures contract in March 2019 to expire on 19th June 2019.

Both contracts are expressed in US dollars and their delivery is made by cash settlement. However, both the size of the contract and the reference for the settlement price differ from each other. The multiplier of the futures contract traded in CBOE was 1 bitcoin and the final settlement value of an expiring futures contract was the official auction price for bitcoin in U.S. dollars determined at 4:00 p.m. Eastern Time (NY Time) on the final settlement date by the Gemini Exchange Auction. The final settlement day takes place two business days (usually a Wednesday) prior to the third Friday of the expiration month.

The multiplier of the bitcoin futures contract traded in CME is 5 bitcoins and the final settlement price is equal to the CME Bitcoin Reference Rate (BRR) at 4:00 p.m. London time on the last Friday of the contract month. BRR is the index composed of the bitcoin quotes from several constituent exchanges. These exchanges are Bitstamp, Coinbase, ItBit and Kraken (since December 2017) and Gemini (since 30 August 2019).

On September 23rd, 2019, the ICE introduced a new regulated future on bitcoin. This contract is negotiated in Bakkt and differs from the two previous contracts in that it is physically settled. The contract size is 1 bitcoin quoted in US dollars and the expiration date is the third Friday of the month. Trading in the expiring contract month ceases at 2:30 pm NY time on the business day prior to the delivery day for the contract month.

We have considered Unix time as the reference to unify the time information of all the markets under analysis, as it is widely used in operating systems and file formats because technically it does not change whatever the location on the globe. Daylight saving times have also been taken into account.

Table 1 shows some descriptive statistics of the bitcoin exchanges. Mean daily returns and volatility measures are very similar in all the exchanges. However, the daily trading volume of BTC does not have a similar pattern across the exchanges. Binance stands out as the exchange with the highest volume and Itibit, with a volume 20 times smaller, has the lowest volume, closely followed by Gemini.

During the coexistence period of CBOE futures with CME futures, the CME monthly volume varied from being less than 20% of the monthly volume traded in CBOE to being more than five times greater. During the coexistence period of CME with Bakkt, the CME monthly volume, on average, was 14 times greater than the monthly volume traded in Bakkt[1], although the physical delivery of Bakkt has become more and more significant and open interest has increased noticeably in this market.

[1] According to the information provided by https://www.theblockcrypto.com/data/crypto-markets/futures and https://es.investing.com/crypto/bitcoin/bitcoin-futures-historical-data on 13th January 2021.

4. Methodology and Results

We have run time series regressions to explore the expiration effect. All the models include as independent variables the appropriate number of lags of the dependent variable to control autocorrelation and the dummy variables for the days of the week from Monday to Saturday to avoid the presence of possible seasonality effects from interfering with the expiration date. We denominated D_M, D_{Tu}, D_W, D_{Th}, D_{Fr} and D_{Sat} these dummy variables related to the days of the week[2]. The models also incorporate a dummy variable designed to detect the effect during the period around expiration. D_{Exp} is the generic expression for this variable that captures the cumulative hourly effect of expiration for a specific futures contract.

We create expiration dummy variables (D_{Exp}) in the following way. The first one, D_1, takes a value of 1 at the hour of the expiration and 0 otherwise. Subsequently D_2 takes a value of 1 both at the hour of expiration and one hour beforehand and 0 otherwise, D_3 takes the value 1 at the hour of expiration and two hours beforehand and 0 otherwise and so on until D_{24} identifies the hour of expiration and 23 hours beforehand. Some of the dummy variables may even correspond to the day before expiration depending on the time-zones. Similarly, we create 24 dummy variables that identify the sequential cumulative effect of the 24 hours after the expiration time and take the value 0 otherwise (from D_{1post}, one hour after expiration, to D_{24post}, up to 24 hours after expiration). These 48 measures to detect the cumulative hourly effect around expiration are based on those used in previous daily studies such as Corredor, Lechon and Santamaria (2001).

We have considered the expiration dates of CME, CBOE and Bakkt separately as well as the joint effect of all of them (taking into account all the expiration dates in all the contracts involved), with the purpose of finding possible differences among them, if any, and the dominant global effect.

Thus, we have finally run 576 models, using 48 alternative cumulative hourly dummies, on 3 variables of analysis (volume, volatility and return), for 4 different

[2] Although some hourly patterns may have been observed in traditional markets with fixed trading hours, bitcoin exchanges operate 24/7 in various time-zones, therefore hourly effects are unlikely.

references of expiration dates depending on the futures market studied (CME, CBOE and Bakkt separately and the joint effect).

4.1. *Effects on Trading Volume*

The model proposed to estimate the effect on the trading volume is the following:

$$TV_{i,t} = \beta_0 + \beta_1 D_M + \beta_2 D_{Tu} + \beta_3 D_W + \beta_4 D_{Th} + \beta_5 D_{Fr} + \beta_6 D_{Sat} + \beta_7 D_{Exp} + \beta_8 Trend + \sum_{j=1}^{5} \beta_{j+8} TV_{i,t-j} + \varepsilon_{i,t} \quad (1)$$

where the TV_{it} dependent variable indicates the trading volume in bitcoins in exchange i and hour t. As is usual in the financial literature, trading volume is measured by taking the natural logarithm of the volume. The use of logarithms stabilizes the variance of the volume, since it is non-negative and tends to be more volatile when volume is high and less volatile when volume is low. The model includes the seasonal and expiration dummy variables as previously defined and five lags of the dependent variable. In addition, this model adds a time trend variable (Trend) that captures the increase in trading volume over time. We have run OLS regressions using Newey-West heteroscedasticity-consistent standard errors and covariance. In all the estimates, the coefficients associated with the lags of the dependent variable and the deterministic trend are significant. Those associated with daily seasonality, with a few exceptions in some exchanges, are also significant. Saturdays stand out as the day with the lowest volume traded.

A summary of the results obtained is shown in Table 2[3]. In the 15 hours prior to expiration of the CME bitcoin futures contract, a significant increase in the trading volume is observed in all the exchanges. This effect starts even sooner in several of them. The strongest increases take place in the hours closest to maturity. A significant reverse effect is observed after the expiration time in 5 out of the 7 markets, with significant negative volume changes, and this effect extends to all the exchanges after

[3] For brevity, each table only shows the results from D_1 to D_{10} and D_{1post} to D_{10post} individually whereas further results are considered to be represented by D_{15}, D_{20} and D_{24} as well as D_{15post}, D_{20post} and D_{24post}, given that each of these variables contains an accumulated effect.

14 hours. The reverse effect in Gemini and Coinbase, two significant markets for American traders, takes more time to be detected.

The pattern of an increase in trading volume in the hours prior to expiration is also observed when analysing the expiration of the CBOE bitcoin future, although the effect is less intense than in the case of the CME expiration. The general increase in all exchanges occurs between 10 and 18 hours prior to expiration. In addition, Coinbase, Itbit, Gemini and Kraken also show an increase in trading during the hours nearest to expiration. The increase in Gemini (the exchange involved in the settlement system of the CBOE contract) is especially significant since the effect is detected up to 24 hours before the time of expiration. In the hour after the expiration, all the exchanges have a significantly lower trading volume and this effect is prolonged for a few more hours, although not as uniformly as in the case of the expiration of the CME nor for as many hours, since after 16 hours the volume in all the exchanges becomes normal. In sum, the volume in the Gemini exchange is the most affected by the CBOE expiration effect, but it is also interesting to note that all the exchanges start to significantly decrease their trading volume shortly after this expiration although the opposite effect before expiration is not always detected shortly before maturity.

The results for the expiration dates of the Bakkt bitcoin future do not follow a uniform pattern. In contrast to the clear increase in trading volume observed when the CME or the CBOE bitcoin futures expire, there is a decrease in trading volume in 4 of the 7 exchanges at the time of the Bakkt expiration and in the previous hours (up to 6 hours beforehand). This effect is more intense in D_2. Two of the exchanges (Gemini and Itbit) have an increase in trading volume from 5-10 hours before expiration. A mixed behaviour is observed in Kraken since in the hour preceding expiration the trading decreases, but this follows a significant increase some hours earlier. In the hours immediately following expiration, the trading volume also decreases significantly in almost all the exchanges, the significant effect lasting longest in Gemini and Itbit. Therefore, the only common pattern that can be found in the three cases is the significant decrease in trading volume after futures expiration.

When the joint effect of all maturities is analysed, a result similar to the combination of the significant coefficients of the CME and CBOE maturities is observed, both when looking at the effect in the hours before maturity and in the hours after it. Furthermore, this result suggests that CME is the most influential futures market.

Since the traded volume gathers the activity of all types of market participants, at least in this first approach the variation detected in trading volume around the expiration cannot be directly attributed to a specific investor type.

Finally, our results indicate that volume effects are identified on constituent and non-constituent exchanges. The usual arbitrage strategies among spot exchanges (cash-and-carry arbitrage) or the herding effects among exchanges could help to explain the trading activity around expiration in all exchanges.

4.2. Effects on Volatility

The concept of volatility is a controversial one in the financial literature. Since volatility is a latent variable and is not directly observable, its computation can be carried out in different ways depending on the use of real data, expectations or conditional information. Historical, realized, implied or conditional volatilities are some of the measures reflecting these choices. In this paper, we analyse the expiration effect on a historical volatility measure in order to observe the effect on the trading data itself[4].

We use the Garman and Klass (GK) estimator of unconditional volatility. Range-based volatility estimators are unbiased and highly efficient relative to other volatility measures and robust to certain types of microstructure noise (Brandt & Diebold, 2006). This measure includes maximum (H_t), minimum (L_t), opening (O_t)

[4] We are aware that other alternatives such as conditional volatilities could also be interesting, especially when it has been proven that the errors in the mean equation follow this conditional structure. We tried to estimate the effect on volatility using conditional volatility models. However, daily seasonality variables in the mean and also in the variance led to estimation problems as the models failed to converge. An alternative to achieve convergence could have been to eliminate daily seasonality dummy variables, but this option does not cater for the possible overlap with the expiration day. In order to be consistent with the general model proposed, we consider the use of unconditional volatility more appropriate in this paper.

and closing (C_t) prices in hour t and computes P_t = ln (H_t/L_t) and Qt= ln (C_t/O_t). Volatility is obtained as follows:

$$\sigma_{GK,t} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left[\frac{1}{2}P_t^2 - (2ln2 - 1)Q_t^2\right]} \tag{2}$$

where n is the number of historical prices used. We use n equal to 1 in our calculation of hourly volatility estimation. As in the case of trading volume, we run OLS regressions with Newey-

West heteroscedasticity-consistent standard errors and covariance. The model estimated is the following:

$$\sigma_{GK_{i,t}} = \beta_0 + \beta_1 D_M + \beta_2 D_{Tu} + \beta_3 D_W + \beta_4 D_{Th} + \beta_5 D_{Fr} + \beta_6 D_{Sat} + \beta_7 D_{Exp} + \\ + \sum_{j=1}^{5} \beta_{j+7}\sigma_{GK_{i,t-j}} + \varepsilon_{i,t} \tag{3}$$

where $\sigma_{GK_{i,t}}$ is the GK volatility in the exchange i in hour t. Daily and expiration dummy variables are the same as the ones defined in the previous section. The models also include five lags of the dependent variable to correct autocorrelation, which is significant in all the estimates, and include dummy variables for daily seasonality. Thursday is the day with the highest volatility and Saturday the lowest, but the effect varies depending on the exchange.

Table 3 presents the results on volatility. Up to 12 hours before maturity of the CME bitcoin future, volatility increases significantly in all the exchanges except Kraken where no effect is observed before maturity. Once the contract negotiation is closed, a significant decrease in the volatility of the spot bitcoin is observed, which lasts for 6 hours but does not extend beyond that time (except in Kraken, where the volatility reduction is noticeable for 8 hours).

All the exchanges showed significantly increased volatility in the hours leading up to the expiration of the CBOE bitcoin future. The greatest movement in prices is detected during the day of expiration, since the significance is observed in the 15 hours prior to maturity. It is noteworthy that the effect is not visible at the final time of maturity, maybe due to the system of settlement by auction. In the hours following the expiration, the exchanges do not react immediately as they take time to significantly reduce their volatility which occurs five hours later, maintaining this effect for about five more hours. The effect does not last longer. Itbit and Kraken do not change their volatility level after the expiration time.

The effect of the expiration of the Bakkt bitcoin futures, once again, differs from the effects of the CME or CBOE futures expiration. The most relevant factor is that volatility in the spot market decreases significantly at the time of expiration, one hour before and one hour later. From that time onwards there is no defined pattern for all the markets. For some exchanges, volatility is significantly lower than the others at some times after maturity, but this effect does not last long. In order to highlight a common pattern for volatility, it can be pointed out that volatility decreases after the expiration time, regardless of the futures contract expiring.

Finally, the aggregation of maturities for the three futures markets offers homogeneous results among exchanges. With some exceptions, from five hours before to 15 hours before the expiration time, volatility increases significantly. After expiration, volatility decreases for ten hours. After that time, the effect vanishes.

The most noticeable effects on volatility generally appear close to the expiration time. These results analysed together with results in trading volume show that the effects are not uniform.

The effects of CME and CBOE maturities are similar in volume and volatility, although with different intensity. Both variables increase before maturity and substantially decrease later. In the case of the Bakkt expirations, when there is an effect before maturity, this effect is negative on trading volume and volatility. However, effects after expiration follow the same direction for all three futures contracts. Differences in the delivery procedure may very likely be the cause of the differences in the results. In traditional markets, most physically delivered futures contracts are offset or rolled forward prior to the last trading day, particularly if the delivery process is complex. This practice in the futures markets could be a feasible explanation for the surprising decrease in activity in spot exchanges before the expiration date in futures contracts with physical delivery, presumably used mainly by hedgers. Conversely, speculators and arbitrageurs are potentially more inclined to use cash-settled futures.

4.3. Effects on Returns

The model proposed to examine the effect on returns is:

$$R_{i,t} = \beta_0 + \beta_1 D_M + \beta_2 D_{Tu} + \beta_3 D_W + \beta_4 D_{Th} + \beta_5 D_{Fr} + \beta_6 D_{Sat} + \beta_7 D_{Exp} + \\ + \sum_{j=1}^{2} \beta_{j+7} R_{i,t-j} + \varepsilon_{i,t} \tag{4}$$

where R_{it} is the return of the exchange i in hour t. The other variables are defined previously and ε_{it} follows a distribution $N(0, \sigma^2_t)$

We use Threshold GARCH models with the threshold order equal to 1 to reflect asymmetric conditional volatility. Following this particular choice, the specification for the conditional variance is given by:

$$\sigma_t^2 = \omega_0 + \omega_1 \sigma_{t-1}^2 + \omega_2 \varepsilon_{t-1}^2 + \omega_3 \varepsilon_{t-1}^2 \gamma_{t-1} \tag{5}$$

where $\gamma_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise.

Table 4 shows a summary of these results. Although not shown in the table for reasons of clarity, two return lags have been included in the mean models since they were found helpful to prevent autocorrelation. Both are significant in all the regression estimates. With respect to the daily seasonality, although the pattern is not coincident in all estimations and exchanges, it is observed that Tuesday returns are significantly lower than on the rest of the days. This also occurs on Fridays in some exchanges. As for conditional volatility, all the coefficients are significant, confirming the appropriateness of the estimation procedure. This equally occurs in more traditional markets, where the asymmetry of negative shocks inducing greater volatility stands out.

When we estimate the effect using the expiration dates for the CME bitcoin futures, we appreciate a clear effect on prices at the maturity time and five hours prior to the expiration time in all the exchanges under analysis. Returns are significantly higher than the mean return at the 1% significance level. The strongest effect is reflected in D_2 and D_1, that is, at the time of the expiration effect and one hour before. After the expiration time, returns are significantly higher for one more hour in five markets. Furthermore, this effect remains some hours later, although less intensely and at a lower confidence level. Nevertheless, it is noticeable that this significant positive effect is repeated 7, 8 and 9 hours after the maturity time, and it can also be perceived 15 hours later in some markets. These results can be attributable to the different time zones where the exchanges operate. European locations may be from 5 to 9 hours ahead of American sites, and Asian locations between 8 and 17 hours ahead. For example, Singapore is 8 hours ahead of London, 13 hours ahead of New York and 16 hours ahead of San Francisco, all cities where the exchanges have their headquarters or main offices. For example, Bitstamp, one of the major platforms for European crypto traders, basically shows the effect prior to the expiration date and shortly after it, with a residual significance in D_{8post}. This finding is compatible with the fact that most of the trading close to this expiration time is European or even Asian, whereas the residual response of late American traders (or even new Asian traders) may be reflected hours later. In fact, the rest of the exchanges under analysis where the effect on returns remains up to D_{15post}, have a significant market share in Asia and America.

The effects in relation to the monthly expiration times of CBOE bitcoin futures are scarce. A negative expiration effect could be detected 3 hours before maturity and 9 hours before maturity for some exchanges, but not all of them. This minor effect on D_9 may be compatible with European and Asian trading, both for the time and for the exchanges involved (Binance and Bitfinex are strong markets in Asia, Bitstamp and Kraken are major markets for European customers). However, it is worth mentioning that these results are mostly significant at the 10% significance level. In particular, the Gemini exchange, involved in fixing the final settlement price, is not affected by this negative effect. No significant pattern is found after maturity. These results do not allow us to confirm a clear effect of the CBOE futures expiration on returns.

Table 4 also shows the results for the monthly expiration date of the Bakkt bitcoin futures. Neither at the expiration time nor at the nearest hours before and after it can we appreciate significant changes in the bitcoin returns for any of the exchanges in our sample. There are some significant negative results in D_{20} and D_{24} and between D_{7post} and D_{10post}. These scarce significant negative results (most of them only significant at a 10% significance level) may be related to time-zone effects, but there is no clear pattern of the Bakkt expiration effect on returns.

Trying to explain the disparity in the results relating to returns, we have also checked whether the expiration dates with a positive/negative effect were coincidentally framed in periods with positive/negative returns. We calculate the accumulated return 15 days before each expiration date and compare it with the expiration date return. The percentage of coincidences between positive 15-day previous returns and positive expiration date returns is 29.4%, 27.7% and 42.8% for CME, CBOE and Bakkt contracts, respectively. The percentage of coincidences between negative 15-day previous returns and negative expiration date returns is, respectively, 26.4%, 22.2% and 28.5%. These statistics indicate that our results are not a consequence of the state of the market, but something else, supporting the idea of a possible expiration effect on returns.

Finally, we study the global effect taking into account the expiration times for the three futures markets under analysis. The results indicate significant positive returns about 5 hours before maturity, and 1 hour after maturity (in five out of seven exchanges), showing a similar pattern to the findings for the CME futures.

To sum up, once again the CME contract is the most dominant in terms of the expiration effects on returns. The strongest effects are detected shortly before or after the maturity time, although there may be some smaller earlier or later effects related to trading in different time zones.

Our prevailing result is an abnormal positive return induced by the CME. Although the financial literature does not show a consensus on expiration effects on returns, previous studies have found results in accordance with ours (see, among others, Chamberlain, Cheung & Kwan, 1989; Chen, Kuo & Huang, 2011 or Sadath & Kamaiah 2011). Typically, this effect is attributed to the unwinding of short arbitrage positions. In the case of bitcoin markets, the unwinding of short arbitrage positions would be possible if the available arbitrage opportunities consisted of selling bitcoin short and buying under-priced futures and, consequently, prices rose at expiration as short arbitrageurs move to unwind their positions and provoke a buy order imbalance. In fact, Lee, El Meslmani and Switzer (2020) report that bitcoin futures underpricing has often been detected at the introduction of futures contracts. Therefore, this could be a feasible explanation for our findings. However, this type of arbitrage strategy is not easily implementable in the bitcoin market: arbitrage operations can be inhibited by price differences constantly changing among constituent exchanges as well as trading frictions (for example, price limits or circuit breakers due to extreme volatility) on the CME futures markets.

On the other hand, we must remember that the spot market is susceptible to price manipulations. Baur and Dimpfl (2019) found that bitcoin spot prices were ahead of CBOE and CME futures prices in terms of price discovery in 2018 because the spot market never closes, whereas the CBOE and CME operate at traditional US trading hours. Speculators (and arbitrageurs) could therefore be interested in determining winning and losing positions on the futures market. Those who buy futures before maturity can try to manipulate spot prices upwards if they are interested in market upturns at maturity (either to liquidate futures at a gain or to avoid negative roll yields when futures markets are in contango[5]). Conversely, speculators (and arbitrageurs) who sell futures before maturity can try to manipulate spot prices downwards if they are interested in market downturns at maturity (either to liquidate futures at a gain or to avoid negative roll yields when futures markets are in backwardation). Contango is more often seen than backwardation. In fact, backwardation appeared during the bearish market conditions in 2018 and the beginning of 2019 (Lee, El Meslmani & Switzer., 2020). Perhaps this fact can help to explain the difference in return results between CBOE maturities and CME maturities. CBOE futures disappeared in the first quarter of 2019, after a bearish market and likely backwardation conditions, whereas a

[5] In this paper, we consider the market is in “contango” when the futures price is above the expected future spot price, and the market is in “backwardation” when the futures price is below the expected future spot price.

significant contango appeared later as the CME took the definitive leadership in bitcoin futures.

In light of our results and previous comments, we suggest that although theoretically speculators´ and arbitrageurs´ joint participation could produce the expiration effect, it is empirically difficult to distinguish the leading role of each of these actors. However, the difficulties mentioned above in carrying out arbitrage operations make it possible to question the prevalence of this type of market participant and highlight the role of speculators at close-to-expiration times.

4.4. Robustness tests

The empirical models in this paper involve different assumptions such as the computation of the variables, the definition of the estimation model or the nature of the information used that could affect the interpretation of the results. We conduct different robustness checks in order to consider some of these sensitive aspects[6].

First, we examine the robustness of the results following a different methodology in the estimation process. The results described above have been found for each of the bitcoin exchanges independently. In order to establish the general effect on all the exchanges, we have run pool estimations using least squares with fixed effects and robust standard errors. This estimation imposes the condition that the coefficients are equal across all exchanges. The aggregation allows an overall assessment. The effect on trading volume is confirmed with the pooled estimation for the CME and CBOE expirations, showing a general positive impact on the volume at the expiration time and some hours before, and a negative effect after expiration. Likewise, the results for the Bakkt expiration are corroborated, given that the pool shows, on the one hand, the negative effect for D_1 and D_2 and, on the other, a positive effect from D_{11} to D_{14} that is consistent with the above-mentioned effects in Gemini, Itbit and Kraken. The negative effect from D_{6post} to D_{10post} is also proven. The global effect on volatility is confirmed, being positive and concentrated in the few hours before expiration and negative for six or seven hours after maturity for the CME

[6] For brevity, these results are not included as tables in the paper, but they are available upon request.

futures, the negative effect concentrated around the Bakkt expiration, and the volatility increasing in the hours previous to the CBOE expiration dates. In the specific case of CME expiration, the results show a significant positive effect on returns in a short time before maturity (about five hours before expiration, although not in the last hour). No effects are detected after then. The results also confirm that CBOE does not show any significant global influence on returns. However, the results do not coincide in the case of Bakkt. This shows significant positive effects on returns from D_7 to D_{24} and D_{1post} that did not appear in the individual analyses. We emphasize that the only clear impact on returns is caused by the expiration of the CME futures.

We also test the robustness of the results to the historical volatility measure. We propose to re-estimate the models using the Parkinson volatility estimator. This measure merely uses the information of maximum (H_t) and minimum (L_t) prices of bitcoin in hour t through the following indicator

$$\sigma_{P,t} = \frac{1}{2\sqrt{ln2}}\sqrt{\frac{1}{n}\sum_{t=1}^{n} P_t^2} \qquad (6)$$

where P_t is calculated as previously and n is the number of historical prices used. The results are practically the same as those discussed for GK volatility.

Finally, although this paper does not report the results with daily data, an exhaustive analysis has been made with the daily information considering possible effects during the week before and after expiration. The results do not allow detection of a clear expiration effect on the days around expiration. This finding highlights the relevance of intraday data. Particularly for markets that operate 24/7 worldwide, the exclusive use of daily data can mask the no-longer-than- a-day effect that futures expiration produces on exchanges available in different time zones.

5. Discussion and Conclusions

This paper studies the monthly expiration effect in the bitcoin markets. The arrival of trading of bitcoin futures in regulated markets is an ideal occasion to try to test this effect on an asset with singular characteristics.

Our results show that around the time of maturity there are significant changes in the trading volume, volatility and returns of bitcoin, an asset traded in many exchanges simultaneously. Therefore, there is a clear expiration effect related to bitcoin futures. The closer to the expiration time (shortly beforehand or afterwards), the more intense these effects are. The prevailing effect on trading volume is that it increases before the expiration date, at least in the case of cash-settled contracts, and decreases later. The volatility pattern is similar, but more concentrated. The effects on returns do not follow a common pattern. In fact, the only clear expiration effect is caused by the CME expiration time.

The expiration dates of the CME futures cause the most noticeable effects. When all the expiration dates are considered, the global results indicate this dominance. This finding may be due not only to the larger trading volume in this market but also to the fact that the CME is the market with the longest life in our analysis.

For all markets and maturities, volatility changes are aligned with the effect detected in trading volume. Volume increases tend to increase volatility and vice versa. However, the effect on volatility is shorter in time than that detected on volume. Both are noticeable some hours before the beginning of the effect on prices. It should be noted that spot markets trade 24/7 worldwide, but some exchanges concentrate significant market shares in a specific area. For example, Binance and Bitfinex are strong markets in Asia, Bitstamp and Kraken are major markets for European customers, and Gemini, Coinbase and Kraken are currently the main crypto exchanges for U.S based crypto traders. Continuous trading along different time zones may help to explain the extension of the effects on volume that, in turn, can induce later effects on volatility and prices.

The fragmentation of the spot markets allows us to detect some differences across exchanges. Given that different platforms worldwide offer different bitcoin prices, we would also expect some differences in their expiration effects. For example, regarding volume effects, large markets such as Binance are less affected than relatively small markets such as Itbit; or for example, Coinbase, a more retail-consumer oriented platform, is also less affected, probably because institutional investors generally focus on other exchanges. From another perspective, Gemini, as an exchange specifically involved in CBOE futures, shows some differences in the effects on returns and volume compared to other exchanges.

As stated before, the overlapping of possible effects from other unregulated futures with the same maturity dates as those of some of the formally regulated futures under analysis, as well as the expiration of other sophisticated products such as options or futures with daily maturity, may also influence the results obtained in the spot markets. However, as pointed out previously, perpetual futures represent the highest percentage of unregulated futures trading and cannot induce an expiration effect as they do not expire, they are generally marked-to-market every 8 hours, and they trade close to the spot price of the underlying cryptocurrency. In addition, regulated futures attract institutional investors, whose robust access to information is likely to sway trading among retail investors and contributes to explaining the expiration effects. Furthermore, the largest unregulated futures market, Binance, was roughly the same size as CME at the end of our sample period in terms of open interest in bitcoin futures ($1,095 billion and $1,16 billion, respectively[7]). Considering that much of Binance´s turnover involves perpetual futures, our results can be mainly attributed to the regulated maturities at the CME. Finally, other expiration dates such as quarterly expiration dates in Binance are assumed not to cause the monthly reactions detected. At most, some weekly or daily maturities could contribute to our results, but this contribution does not seem to be significant as we do not detect any effect on non-expiry dates at the CME, CBOE or Bakkt that could coincide with more frequent expiration dates in unregulated markets[8].

It is worth highlighting that the use of intraday data allows detection of the persistence of the changes in the market variables throughout the expiration day or on the previous or subsequent day, knowing that the effect does not last longer than 24 hours. This means that tests with daily data would hide much of the information that has been detected in this work. Intraday data provide efficiency to the analysis. Likewise, the analysis of individual exchanges and individual futures contracts is

[7] https://www.coinglass.com/BitcoinOpenInterest, as of December 1st 2020.

[8] Kraken also has monthly expiration days coinciding with CME monthly expirations, but we estimate that Kraken´s open interest for such bitcoin futures is at most 1.5% of the CME monthly futures. Furthermore, Kraken does not show any significant different effects.

helpful, given the different sensitivities to some variables such as time-zone, market size or crypto-traders´ preferences. Joint estimations may also mask particular effects if there is a very heavily traded futures contract and/or bitcoin exchanges are considered as a whole.

The introduction of bitcoin futures contracts in regulated markets leads to an expected increase in institutional investors´ trading. The evidence presented in this paper suggests that this has occurred especially because of the CME contracts. According to Arcane Research[9], as of December 29th 2020, CME is the largest contributor to the open interest in the BTC futures market. Coinciding with the fact that during the second half of 2020 many institutional investors announced or recommended bitcoin allocations, CME open interest at the end of 2020 was more than 60 times greater than the open interest in Bakkt futures. This may be due to the multiplier associated with the futures contract specifications. In the case of CME, the five bitcoins size versus the 1 bitcoin size of the CBOE or Bakkt contracts may amplify the effect. Institutional investors tend to be sophisticated investors compared with retail investors. This means that institutional traders may find arbitrage and speculation opportunities more often than retail traders. The institutional participation may strengthen the expiration effect. These explanations are also consistent with the fact that CME expirations are dominant.

This study has several implications. We believe that this research throws some light on cryptocurrencies, on some anomalies that cast doubts on market efficiency, and on how bitcoin pricing can be stable. Should bitcoin become a generalized means of payment, it would be of interest to control such pricing anomalies. Regulators must be aware of the bitcoin market fragmentation. If an expiration effect is detected, there may be exploitable anomalies from which some participants can take advantage. Furthermore, effective regulations require consensual actions among the different agents involved in the individual markets, and empirical evidence can help to determine the areas where regulatory action or supervision is required.

[9] Arcane Research weekly update, 2020 summary. Downloadable at https://research.arcane.no/the-weekly-update on 10th January 2021

Our work brings together two branches of financial literature: the analysis of market anomalies and the study of bitcoin. Although the literature has already reported introduction effects and price discovery processes in bitcoin markets, not very much is known about the peculiar case of the expiration effect on bitcoin. We empirically confirm a clear anomaly in the spot market when the futures expiration date arrives, a phenomenon which is clearly manifested in the hours around the expiration. However, the complex conjunction of many factors involved in the determination of this effect does not allow us to identify the driving causes for it. Although some clues have been suggested in this paper, the peculiarities of the bitcoin markets hinder such an analysis.

The course of time will see future research in this field. One possible line of study could be to observe how the expiration effect changes with the recent introduction of regulated markets of bitcoin options or micro bitcoin futures. Undoubtedly, more extensive periods will enable better analysis of how the expiration effect changes as the bitcoin futures markets grow and become more mature.

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Table 1. Descriptive Daily Statistics.

	Binance	**Bitfinex**	**Bitstamp**	**Coinbase**	**Gemini**	**Itbit**	**Kraken**
A. Trading volume BTC							
Mean	45,110	17,716	9,065	12,887	3,001	2,004	6,148
Std.Dev.	31,068	19,928	7,006	10,487	3,032	2,582	4,634
Max	402,202	189,674	70,961	117,495	29,967	36,419	45,111
Min	-	-	-	-	-	-	-
B. Volatility							
Mean	0.03366	0.03354	0.03416	0.03361	0.03348	0.03473	0.03492
Std.Dev.	0.02670	0.02517	0.02593	0.02654	0.02622	0.05191	0.02823
Max	0.30709	0.26914	0.29845	0.29759	0.28826	1.25368	0.28754
Min	-	-	-	-	-	-	-
C. Returns							
Mean	0.00026	0.00026	0.00025	0.00026	0.00024	0.00028	0.00025
Std.Dev.	0.04081	0.04088	0.04145	0.04128	0.04143	0.04088	0.04122
Max	0.15868	0.15941	0.16935	0.16966	0.17005	0.16887	0.16966
Min	-0.50261	-0.49190	-0.49397	-0.49123	-0.49641	-0.45199	-0.49335

Note: This table shows the main descriptive statistics of daily data: trading volume, Garman-Klass volatility measure and returns for spot markets. Columns show the results for the different exchanges, Binance, Bitfinex, Bitstamp, Coinbase, Gemini, Itbit and Kraken, respectively.

Table 2. Expiration effect on hourly trading volume

	Expiration of CME bitcoin futures							Expiration of CBOE bitcoin futures						
	Binance	Bitfinex	Bitstamp	Coinbase	Gemini	Itbit	Kraken	Binance	Bitfinex	Bitstamp	Coinbase	Gemini	Itbit	Kraken
D_{24}	0.0155	0.0290	0.0352	0.0379*	0.0241	0.0688*	0.0544**	-0.0133	0.0182	0.0179	0.0258	0.0784*	0.0618	0.0261
D_{20}	0.0364*	0.0609**	0.0619**	0.0411*	0.0116	0.0768*	0.0617**	-0.0140	0.0515	0.0620*	0.0508	0.1301***	0.1000*	0.0562
D_{15}	0.0530**	0.0711**	0.1198***	0.0540**	0.1046***	0.1638***	0.0886***	0.0915**	0.1653***	0.1106***	0.1088***	0.2086***	0.1923***	0.1464***
D_{10}	0.0999***	0.2101***	0.26141**	0.1692***	0.1673**	0.2814***	0.2146***	0.1016*	0.1512**	0.0700	0.2123***	0.3348***	0.2473***	0.1849***
D_{9}	0.091**	0.1924***	0.2413***	0.1616***	0.1753***	0.3245***	0.2001***	0.1053	0.1145	0.0574	0.2140***	0.3351***	0.2269***	0.1781***
D_{8}	0.0743*	0.1542***	0.2011***	0.1681***	0.1643***	0.3590***	0.1859***	0.1117	0.1116	0.0527	0.2061***	0.3552***	0.2123**	0.1735***
D_{7}	0.0915***	0.1515***	0.1904***	0.2026***	0.2069***	0.3254***	0.1963***	0.0639	0.1151	0.0478	0.1996***	0.3627***	0.1884*	0.1563**
D_{6}	0.1086***	0.1572***	0.1830***	0.2518***	0.2814***	0.3986***	0.2208***	0.0449	0.0991	0.0359	0.1730***	0.3582***	0.1581	0.1449**
D_{5}	0.1268***	0.1333**	0.1849***	0.2756***	0.3073***	0.4430***	0.2210***	0.0122	0.0995	0.0291	0.1393***	0.3198***	0.1562	0.1086*
D_{4}	0.1261**	0.1204**	0.1588***	0.2579***	0.3278***	0.4462***	0.2185***	0.0024	0.1072	0.0295	0.1251**	0.3110***	0.1348	0.0929
D_{3}	0.1269***	0.0802	0.1826***	0.2925***	0.3869***	0.4200***	0.2555***	0.0344	0.1851*	0.0893	0.1502**	0.4122***	0.1432	0.1185
D_{2}	0.2035***	0.1715*	0.2755***	0.3566***	0.4452***	0.5397***	0.2984***	0.0270	0.2129**	0.0375	0.1618**	0.5957***	0.2087*	0.0948
D_{1}	**0.1838****	**0.1435**	**0.0710**	**0.2491*****	**0.3001****	**0.3413****	**0.3161*****	**0.0172**	**0.2575***	**0.0134**	**0.0700**	**1.1069*****	**0.3484***	**0.0813**
D_{1post}	-0.1312*	-0.1661	-0.2632**	-0.0643	-0.0250	-0.1202	-0.0761	-0.2584**	-0.3995**	-0.4884***	-0.3157**	-0.8796***	-0.9730***	-0.4098***
D_{2post}	-0.2142***	-0.1737*	-0.2156***	-0.0754	0.0219	-0.1283	-0.1470**	-0.0929	-0.1584*	-0.2025**	-0.1043	-0.4324***	-0.4197***	-0.1364
D_{3post}	-0.2197***	-0.2110***	-0.2267***	-0.0631	0.0419	-0.2134**	-0.1091**	-0.1092*	-0.1284	-0.2187***	-0.1011	-0.3304***	-0.2920***	-0.1527*
D_{4post}	-0.1714***	-0.1812***	-0.1605***	-0.0272	0.0673	-0.1881*	-0.0804**	-0.0862*	-0.1561**	-0.1875***	-0.0962*	-0.2768***	-0.1862**	-0.1525**
D_{5post}	-0.1426***	-0.1442***	-0.1752***	-0.0113	0.1343***	-0.2481***	-0.0562	-0.0519	-0.1165*	-0.1374**	-0.0568	-0.2692***	-0.1067	-0.1351**
D_{6post}	-0.1603***	-0.1192***	-0.2303***	-0.0381	0.0409	-0.4490***	-0.0733**	-0.0347	-0.1365**	-0.1145**	-0.0390	-0.1968**	-0.0994	-0.1477**
D_{7post}	-0.1325***	-0.1290**	-0.2111***	-0.0387	0.0056	-0.4050***	-0.0717*	-0.0237	-0.0964	-0.1119***	-0.0494	-0.1624**	-0.0854	-0.1294**
D_{8post}	-0.1153***	-0.1105**	-0.2163***	-0.0544*	-0.0499	-0.3379***	-0.0772**	-0.0254	-0.1071*	-0.1004**	-0.0676	-0.1297*	-0.0643	-0.1567***
D_{9post}	-0.0909***	-0.0945**	-0.1816***	-0.0505	-0.0763	-0.2553***	-0.0518	-0.0399	-0.1084*	-0.1035**	-0.0910**	-0.1511**	-0.1008	-0.1802***
D_{10post}	-0.0867***	-0.0928**	-0.1603***	-0.0399	-0.0804	-0.2405***	-0.0659*	-0.0489*	-0.1344**	-0.1099***	-0.1337***	-0.1903***	-0.1297**	-0.1706***
D_{15post}	-0.0703***	-0.0786**	-0.1250***	-0.0914***	-0.1087**	-0.2007***	-0.0988***	-0.0028	-0.0524	-0.0331	-0.0900***	-0.0970	-0.0504	-0.0973**
D_{20post}	-0.0443**	-0.0138	-0.0548	-0.0858***	-0.1046***	-0.1680***	-0.0374	0.0165	0.0044	0.0064	-0.0454	-0.0095	0.0195	-0.0058
D_{24post}	-0.0117	0.0214	-0.0287	-0.0233	-0.0221	-0.0995*	-0.0091	0.0016	-0.0042	-0.0081	-0.0053	0.0386	0.0366	-0.0036

Table 2. Expiration effect on hourly trading volume. Continuation

	Expiration of Bakkt bitcoin futures							Expiration of all bitcoin futures						
	Binance	Bitfinex	Bitstamp	Coinbase	Gemini	Itbit	Kraken	Binance	Bitfinex	Bitstamp	Coinbase	Gemini	Itbit	Kraken
D_{24}	-0.0071	-0.0383	-0.0339	-0.0118	0.0173	-0.0644	-0.0113	0.0076	0.0173	0.0203	0.0266*	0.0384	0.0424	0.0349*
D_{20}	-0.0028	-0.0638	-0.0485	-0.0286	0.0160	-0.0479	-0.0192	0.0195	0.0386	0.0445**	0.0325**	0.0468*	0.0649**	0.0464**
D_{15}	0.0334	0.0376	0.0669	0.0093	0.0959	-0.0172	0.0657	0.0630***	0.0949***	0.1101***	0.0624***	0.1323***	0.1425***	0.1022***
D_{10}	-0.0111	-0.0280	-0.0438	0.0635	0.1934***	0.1702	0.0822*	0.0786***	0.1475***	0.1463***	0.1599***	0.2195***	0.2498***	0.1795***
D_{9}	-0.0366	-0.0750	-0.0694	0.0589	0.1772***	0.2174**	0.0634	0.0703***	0.1186***	0.1266***	0.1556***	0.2201***	0.2739***	0.1661***
D_{8}	-0.0593	-0.1088	-0.0915	0.0672	0.2137***	0.2163*	0.0640	0.0589*	0.0914***	0.0998***	0.1583***	0.2275***	0.2856***	0.1572***
D_{7}	-0.0426	-0.1053	-0.0748	0.0714	0.2864***	0.3434**	0.0964*	0.0582**	0.0915**	0.0960***	0.1748***	0.2659***	0.2843***	0.1645***
D_{6}	-0.1035**	-0.1738**	-0.1182*	0.0321	0.2847***	0.2838*	0.0240	0.0491*	0.0756*	0.0803**	0.1843***	0.3021***	0.2996***	0.1587***
D_{5}	-0.1086**	-0.2136**	-0.1503**	0.0058	0.2546***	0.2187	0.0041	0.0485*	0.0554	0.0728**	0.1817***	0.2984***	0.3088***	0.1445***
D_{4}	-0.1071*	-0.2607**	-0.1142	0.0079	0.2436***	0.2051	0.0177	0.0465	0.0411	0.0671*	0.1694***	0.3051***	0.3008***	0.1418***
D_{3}	-0.1481**	-0.2514**	-0.1889**	-0.0678	0.1737*	0.1607	-0.0384	0.0472	0.0439	0.0807*	0.1780***	0.3488***	0.2801***	0.1555***
D_{2}	-0.2678***	-0.4063***	-0.3637***	-0.1867***	0.0715	0.0513	-0.2139**	0.0109	0.0448	0.0499**	0.0380**	0.0537*	0.0827**	0.0518**
D_{1}	**-0.2493*****	**-0.2536****	**-0.2948*****	**-0.1304***	**0.0594**	**-0.0506**	**-0.1435**	**0.0508**	**0.0959**	**-0.0229**	**0.1208****	**0.4686*****	**0.2563****	**0.1545***
D_{1post}	-0.0296	0.1318	0.0101	-0.0104	0.1055	0.0843	-0.0015	-0.1351**	-0.1621*	-0.2642***	-0.1190**	-0.2306***	-0.3348***	-0.1503**
D_{2post}	-0.0290	0.0798	0.0229	0.0404	0.1195	0.0725	0.0559	-0.1324***	-0.1110	-0.1582***	-0.0563	-0.0829	-0.1833**	-0.1008**
D_{3post}	-0.1277**	-0.1850	-0.1168	-0.0301	0.0478	-0.3559*	-0.0236	-0.1613***	-0.1778***	-0.1978***	-0.0643**	-0.0612	-0.2724***	-0.1029***
D_{4post}	-0.1164**	-0.1422	-0.1442*	-0.0356	0.0445	-0.4297**	-0.0692	-0.1277***	-0.1604***	-0.1614***	-0.0459*	-0.0346	-0.2390***	-0.0975***
D_{5post}	-0.0941**	-0.1575*	-0.1786**	-0.0483	-0.2910**	-0.3736**	-0.0961	-0.0987***	-0.1343***	-0.1624***	-0.0296	-0.0690	-0.2340***	-0.0860***
D_{6post}	-0.0779*	-0.1497*	-0.1565**	-0.0411	-0.4099***	-0.2607**	-0.0820	-0.1005***	-0.1268***	-0.1808***	-0.0370	-0.1213**	-0.3136***	-0.0961***
D_{7post}	-0.0784**	-0.1120	-0.1515**	-0.0501	-0.2574**	-0.2798**	-0.0831	-0.0842***	-0.1134***	-0.1700***	-0.0424*	-0.0962**	-0.2900***	-0.0910***
D_{8post}	-0.0542	-0.0969	-0.1284*	-0.0368	-0.2078**	-0.2608**	-0.0723	-0.0713***	-0.1042***	-0.1649***	-0.0529**	-0.1049***	-0.2441**	-0.0994***
D_{9post}	-0.0639*	-0.1209**	-0.1707***	-0.0539	-0.2022**	-0.2844**	-0.1130*	-0.0655***	-0.1019***	-0.1572***	-0.0613***	-0.1238***	-0.2157***	-0.1016***
D_{10post}	-0.0436	-0.1011*	-0.1279**	-0.0364	-0.1806**	-0.2901***	-0.1206**	-0.0620***	-0.1042***	-0.1391***	-0.0642***	-0.1307***	-0.2168***	-0.1076***
D_{15post}	0.0096	0.0178	-0.0052	-0.0643*	-0.1835***	-0.2597***	-0.0629	-0.0310**	-0.0494*	-0.0720***	-0.0847***	-0.1169***	-0.1626***	-0.0908***
D_{20post}	0.0105	0.0038	0.0052	-0.0263	-0.1073*	-0.1751**	-0.0288	-0.0130	-0.0028	-0.0225	-0.0611***	-0.0730***	-0.1071***	-0.0253
D_{24post}	0.0001	-0.0187	-0.0086	-0.0104	-0.0654	-0.1131	-0.0245	-0.0023	0.0084	-0.0161	-0.0137	-0.0068	-0.0555*	-0.0091

Note: This table contains a summary with the coefficients and statistical significance of the variable of interest to test the expiration effect. All regressions include week-daily dummy variables, trend variable and dependent lags to adjust autocorrelation. Trading volume is the logarithm transformed of bitcoin traded. Columns show the results for the different exchanges, Binance, Bitfinex, Bitstamp, Coinbase, Gemini, Itbit and Kraken, respectively. ***, ** and * denote coefficients significant at the 1, 5 and 10 per cent level, respectively.

Table 3. Expiration effect on hourly volatility

	Expiration of CME bitcoin futures							**Expiration of CBOE bitcoin futures**						
	Binance	Bitfinex	Bitstamp	Coinbase	Gemini	Itbit	Kraken	Binance	Bitfinex	Bitstamp	Coinbase	Gemini	Itbit	Kraken
D_{24}	0.0028	0.0023	0.0039	0.0054	0.0023	0.0135	-0.0111	0.0525	0.0433	0.0402	0.0440	0.0408	0.0637*	0.0951
D_{20}	0.0177	0.0175	0.0156	0.0166	0.0143	0.0144	-0.0087	0.0514	0.0524*	0.0546*	0.0453	0.0521	0.0612	0.1003
D_{15}	0.0123	0.0171	0.0155	0.0147	0.0134	0.0163	-0.0155	0.1005***	0.099***	0.0989**	0.0998**	0.1018**	0.1151**	0.1543**
D_{10}	0.0555**	0.0608**	0.0634***	0.0609**	0.0568**	0.0744**	0.0388	0.1266***	0.0951**	0.1058**	0.1210**	0.1250**	0.1365**	0.1991**
D_{9}	0.0636***	0.0659**	0.068***	0.0692**	0.0663**	0.0853***	0.0521	0.1302***	0.0888**	0.0975**	0.1131**	0.1177**	0.1285**	0.1928**
D_{8}	0.0594**	0.0572*	0.0633**	0.0670**	0.0610**	0.0796**	0.0549	0.1431**	0.0972**	0.1071*	0.1200*	0.1287**	0.1396**	0.2019**
D_{7}	0.0542**	0.00518	0.0598*	0.0637*	0.0565*	0.0720*	0.0512	0.1412**	0.1034*	0.1136*	0.1189*	0.1258**	0.1476**	0.2087**
D_{6}	0.0601**	0.0610	0.0647*	0.0696*	0.0653*	0.0868**	0.0634	0.1490**	0.1119**	0.1153*	0.1192*	0.1321**	0.1651**	0.2160**
D_{5}	0.0697**	0.0748*	0.0707*	0.0768*	0.0726*	0.0907*	0.0786	0.1132*	0.0976*	0.0988*	0.0990**	0.1025**	0.1328**	0.2001**
D_{4}	0.0525	0.0594	0.0532	0.0575	0.0538	0.0756	0.0586	0.0783	0.0738	0.0647	0.0787	0.0678	0.1088	0.1630
D_{3}	0.0637	0.0703	0.0597	0.0665	0.0689	0.0956	0.0656	0.1880*	0.1587*	0.1521*	0.1614*	0.1603*	0.1738*	0.2513*
D_{2}	0.1392*	0.1578	0.1426	0.1472	0.1463	0.1894*	0.1398	0.1744**	0.1417**	0.1133*	0.1286*	0.1336**	0.1914*	0.2201*
D_{1}	**0.228***	**0.2452**	**0.2201**	**0.2514**	**0.2419**	**0.3418***	**0.2686**	**0.0645**	**0.0510**	**0.0036**	**0.0475**	**0.0148**	**0.0825**	**0.1266**
D_{1post}	-0.0887	-0.0941	-0.1135*	-0.1130	-0.1072	-0.1192*	-0.0753	-0.0178	-0.0821	-0.1769	-0.1833	-0.1637	-0.0423	-0.1169
D_{2post}	-0.1618***	-0.1260***	-0.1440***	-0.1431***	-0.1384***	-0.1579***	-0.1159**	-0.0158	-0.0411	-0.0671	-0.0966	-0.0534	-0.0207	0.0077
D_{3post}	-0.1504***	-0.1306***	-0.1316***	-0.1268***	-0.1256***	-0.1497***	-0.1204***	-0.0733	-0.0554	-0.0871	-0.1137	-0.1006	-0.0410	-0.0276
D_{4post}	-0.1121***	-0.1114***	-0.1062***	-0.0945***	-0.0996***	-0.1251***	-0.1101***	-0.0779	-0.0699	-0.0686	-0.1007	-0.0721	-0.0422	-0.0227
D_{5post}	-0.0835***	-0.0912***	-0.0798***	-0.0698**	-0.0694***	-0.0854***	-0.1082***	-0.0864**	-0.0725*	-0.0751*	-0.0977**	-0.0833*	-0.0577	-0.0270
D_{6post}	-0.0728**	-0.0702**	-0.0719**	-0.0655**	-0.0624**	-0.0723**	-0.1188***	-0.0690*	-0.0615	-0.0674	-0.0828*	-0.0695	-0.0535	-0.0245
D_{7post}	-0.0311	-0.0345	-0.0350	-0.0334	-0.0284	-0.0400	-0.0876**	-0.0570	-0.0539	-0.0671*	-0.0747*	-0.0647*	-0.0478	-0.0207
D_{8post}	-0.0303	-0.0323	-0.0392	-0.0378	-0.0264	-0.0437	-0.0800**	-0.0507	-0.0470	-0.0652*	-0.0665*	-0.0562	-0.0466	-0.0202
D_{9post}	-0.0116	-0.0197	-0.0201	-0.0015	-0.0026	-0.0217	-0.0568	-0.0578*	-0.0537*	-0.0699**	-000731**	-0.0673**	-0.0542	-0.0335
D_{10post}	-0.0163	0.0011	-0.0056	0.0040	0.0168	-0.0010	-0.0282	-0.0657**	-0.0587**	-0.0698**	-0.0732**	-0.0687**	-0.0527	-0.0416
D_{15post}	-0.0292	-0.0175	-0.0234	-0.0223	-0.0140	-0.0229	-0.0396	-0.0160	-0.0117	-0.0199	-0.0280	-0.0210	-0.0069	0.0090
D_{20post}	-0.0110	-0.0040	-0.0051	-0.0069	-0.0047	-0.0034	-0.0235	0.0037	0.0122	-0.0009	-0.0111	-0.0001	0.0151	0.0298
D_{24post}	-0.0041	-0.0013	-0.0012	-0.0012	-0.0008	0.0005	-0.0126	-0.0027	0.0027	-0.0044	-0.0096	-0.0011	0.0077	0.0283

Table 3. Expiration effect on hourly volatility. Continuation

	Expiration of Bakkt bitcoin futures							**Expiration of all bitcoin futures**						
	Binance	Bitfinex	Bitstamp	Coinbase	Gemini	Itbit	Kraken	Binance	Bitfinex	Bitstamp	Coinbase	Gemini	Itbit	Kraken
D_{24}	-0.0136	-0.0126	-0.0109	-0.0110	-0.0067	-0.0031	0.0240	0.0114	0.0075	0.0086	0.0119	0.0092	0.0164	0.0203
D_{20}	-0.0333	-0.0305	-0.0244	-0.0287	-0.0242	-0.0222	-0.0007	0.0155	0.0150	0.0166	0.0150	0.0157	0.0159	0.0163
D_{15}	-0.0078	-0.0019	0.0004	-0.0040	0.0019	0.0052	0.0360	0.0315**	0.0338**	0.0343**	0.0346**	0.0347**	0.0356	0.0387*
D_{10}	-0.0275	-0.0182	-0.0177	-0.0170	-0.0125	-0.0024	0.0922	0.0562***	0.0511**	0.0564***	0.0611***	0.0596***	0.0828**	0.0734***
D_{9}	-0.0331	-0.0234	-0.0193	-0.0209	-0.0140	-0.0067	0.1028	0.0600***	0.0506**	0.0556***	0.0620***	0.0618***	0.0887**	0.0752***
D_{8}	-0.0513	-0.0427	-0.0345	-0.0390	-0.0283	-0.0223	0.0917	0.0572**	0.0441*	0.0523**	0.0586**	0.0589**	0.0894**	0.0717**
D_{7}	-0.0360	-0.0278	-0.0239	-0.0248	-0.0146	-0.0069	0.1235	0.0568**	0.0459*	0.0543**	0.0592**	0.0582**	0.0942*	0.0728**
D_{6}	-0.0558	-0.0494	-0.0438	-0.0454	-0.0332	-0.0216	-0.0753	0.0577**	0.0486*	0.0534*	0.0581*	0.0609**	0.0637	0.0825**
D_{5}	-0.0043	-0.0493	-0.0414	-0.0451	-0.0275	-0.0273	-0.0569	0.0530**	0.0516*	0.0524*	0.0563**	0.0574**	0.0732*	0.0746**
D_{4}	-0.0413	-0.0278	-0.0254	-0.0329	-0.0164	0.0006	-0.0229	0.0377	0.0420	0.0377	0.0437	0.0409	0.0576	0.0665*
D_{3}	-0.0434	-0.0402	-0.0416	-0.0443	-0.0220	-0.0150	-0.0107	0.0726*	0.0682	0.0620	0.0687	0.0728	0.0869	0.0923*
D_{2}	-0.2275***	-0.2272***	-0.2353***	-0.2281***	-0.1977***	-0.2143***	-0.1657**	0.0218	0.0220	0.0216	0.0194	0.0208	0.0224	0.0239
$\mathbf{D_{1}}$	**-0.2032*****	**-0.2143*****	**-0.1939*****	**-0.1856*****	**-0.1787*****	**-0.1941*****	**-0.1400**	**0.0910**	**0.0927**	**0.0706**	**0.1035**	**0.0868**	**0.1449**	**0.1560**
D_{1post}	-0.1397**	-0.1406**	-0.089**	-0.1146**	-0.1256**	-0.1289**	-0.1538**	-0.0749	-0.1003**	-0.1291***	-0.1327**	-0.1257**	-0.1040*	-0.1066*
D_{2post}	-0.0371	-0.0298	-0.0051	-0.0154	-0.0277	-0.0304	-0.0815	-0.0948**	-0.0853**	-0.0979***	-0.1059***	-0.0931***	-0.0769*	-0.1026**
D_{3post}	-0.0520	-0.0630	-0.0492	-0.0485	-0.0583	-0.0605	-0.1172	-0.1100***	-0.0992***	-0.1057***	-0.1091***	-0.1065***	-0.0995***	-0.1093***
D_{4post}	-0.0535	-0.0514	-0.0491	-0.0451	-0.0502	-0.0598*	-0.1147*	-0.0916***	-0.0903***	-0.0868***	-0.0875***	-0.0835***	-0.0907***	-0.0955***
D_{5post}	-0.0400	-0.0421	-0.0358	-0.0364	-0.0618*	-0.0468	-0.1018	-0.0760***	-0.0783***	-0.0719***	-0.0718***	-0.0731***	-0.0878***	-0.0762***
D_{6post}	-0.0323	-0.0371	-0.0322	-0.0280	-0.0703**	-0.0333	-0.0879	-0.0645***	-0.0636***	-0.0649***	-0.0637***	-0.0678***	-0.0898***	-0.0653***
D_{7post}	-0.041*	-0.0447*	-0.0411*	-0.0372	-0.0624**	-0.0421	-0.0960	-0.0421**	-0.0450**	-0.0479**	-0.0470**	-0.0475**	-0.0745**	-0.0489**
D_{8post}	-0.0233	-0.0310	-0.0223	-0.0201	-0.0365	-0.0288	-0.0736	-0.0360**	-0.0389**	-0.0454**	-0.0431**	-0.0384*	-0.0657**	-0.0474**
D_{9post}	-0.0371	-0.0441*	-0.0388	-0.0361	-0.049**	-0.0424	-0.0890	-0.0314*	-0.0371**	-0.0402**	-0.0366**	-0.0316*	-0.0607**	-0.0408**
D_{10post}	-0.0304	-0.0367	-0.0337	-0.0300	-0.0420*	-0.0376	-0.1007*	-0.0348**	-0.0261	-0.0315*	-0.0253	-0.0203	-0.0502	-0.0287
D_{15post}	-0.0056	-0.0112	-0.0122	-0.0156	-0.0161	-0.0189	-0.0790	-0.0224*	-0.0168	-0.0215	-0.0228	-0.0168	-0.0364	-0.0224
D_{20post}	-0.0096	-0.0134	-0.0101	-0.0164	-0.0175	-0.0193	-0.0760	-0.0080	-0.0033	-0.0060	-0.0098	-0.0062	-0.0215	-0.0056
D_{24post}	-0.0150	-0.0186	-0.0172	-0.0219	-0.0225	-0.0265	-0.0801	-0.0075	-0.0057	-0.0065	-0.0075	-0.0055	-0.0169	-0.0072

Note: This table contains a summary with the coefficients and statistical significance of the variable of interest to test the expiration effect. Coefficients are multiplied by 10^2. All regressions include week-daily dummy variables and dependent lags to adjust autocorrelation. Columns show the results for the different exchanges, Binance, Bitfinex, Bitstamp, Coinbase, Gemini, Itbit and Kraken, respectively. ***, ** and * denote coefficients significant at the 1, 5 and 10 per cent level, respectively.

Table 4. Expiration effect on hourly returns

	Expiration of CME bitcoin futures							Expiration of CBOE bitcoin futures						
	Binance	Bitfinex	Bitstamp	Coinbase	Gemini	Itbit	Kraken	Binance	Bitfinex	Bitstamp	Coinbase	Gemini	Itbit	Kraken
D_{24}	0.0000	0.0002	0.0089	0.0070	0.0029	0.0271	0.0063	0.0020	-0.0107	0.0180	0.0210	0.0206	0.0207	0.0056
D_{20}	-0.0110	-0.0099	-0.0053	-0.0086	-0.0126	0.0210	-0.0103	-0.0178	-0.0385	-0.0044	-0.0026	-0.0016	0.0026	-0.0123
D_{15}	0.2825***	0.3065***	0.2744***	0.2989***	0.3139***	0.3756***	0.3124***	-0.0288	-0.0597*	-0.0042	-0.0034	-0.0003	0.0012	-0.0185
D_{10}	0.0142	0.0357	0.0317*	0.0324*	0.0243	0.0427*	0.0353	-0.0142	-0.0400	-0.0055	-0.0039	0.0097	-0.0009	-0.0175
D_{9}	0.0060	0.0261	0.0327*	0.031*	0.0215	0.0478**	0.0355	-0.0632*	-0.0896***	-0.0493*	-0.0466	-0.0287	-0.0401	-0.0638**
D_{8}	0.0334	0.0543**	0.0673***	0.0634***	0.0491**	0.0636**	0.0699***	-0.0406	-0.0736**	-0.0206	-0.0167	-0.0028	-0.0133	-0.0382
D_{7}	0.0107	0.0254	0.0407**	0.0393**	0.0333*	0.0441*	0.0464**	-0.0373	-0.0593	-0.0218	-0.0209	-0.0080	-0.0138	-0.0348
D_{6}	0.0281	0.0504**	0.0593***	0.0477**	0.0412**	0.0609**	0.058**	-0.0386	-0.0520	-0.0415	-0.0487	-0.0354	-0.0553	-0.0344
D_{5}	0.1206***	0.1828***	0.1947***	0.1747***	0.1741***	0.1616***	0.1856***	-0.0201	-0.0396	-0.0178	-0.0183	-0.0100	-0.0231	-0.0233
D_{4}	0.098**	0.1356***	0.1565***	0.1182***	0.1259***	0.1305***	0.1407***	-0.0565	-0.0768	-0.0630	-0.0576	-0.0465	-0.0584	-0.0629
D_{3}	0.1396***	0.2029***	0.1970***	0.1651***	0.2004***	0.1973***	0.2066***	-0.0926*	-0.1191**	-0.0901*	-0.1012*	-0.0891	-0.0942*	-0.0966*
D_{2}	0.3496***	0.4927***	0.5221***	0.4637***	0.4584***	0.3740***	0.4717***	-0.0280	0.0233	0.0375	0.0396	0.0064	0.0501	0.0359
D_{1}	**0.2825*****	**0.3065*****	**0.2744*****	**0.2989*****	**0.3139*****	**0.3756*****	**0.3124*****	**-0.0218**	**0.0910**	**0.0257**	**0.0705**	**0.0698**	**0.0629**	**0.0624**
D_{1post}	0.1178	0.1907**	0.1750**	0.2047***	0.1884***	0.1607	0.2177***	0.1842	0.1929	0.1857	0.0593	0.0262	0.0119	-0.0042
D_{2post}	0.0455	0.0888	0.0230	0.0288	0.0976	0.0622	0.0863	0.0614	0.2712	0.0413	0.1444	0.0059	0.2113	0.0396
D_{3post}	0.0158	0.0352	0.0061	0.0153	0.0278	0.0477	0.0310	0.1037	0.0903	0.1103	0.1124	0.1105	0.1363	0.0249
D_{4post}	0.0259	0.0551	0.0485	0.0308	0.0558	-0.0012	0.0302	0.0574	0.1391	0.0811	0.1259	0.0468	0.0504	0.0521
D_{5post}	0.0521	0.0569	0.0423	0.0280	0.0609	0.0752	0.0695	0.0634	-0.0054	0.0878	0.0132	0.0958	-0.0143	0.0165
D_{6post}	0.0549	0.0922*	0.0429	0.0803	0.1020	0.1237*	0.0939*	0.0663	0.1184	0.1210	0.0560	0.0651	0.1133	0.0824
D_{7post}	0.0559*	0.0680**	0.0491	0.0636*	0.0569*	0.0765**	0.0731**	0.0057	0.0553	0.0358	0.0687	0.0694	0.1136	0.0556
D_{8post}	0.0658*	0.0072**	0.0624*	0.0696**	0.0646**	0.0882***	0.0844***	0.0369	0.0269	0.0283	0.0558	0.0549	-0.0294	0.0827
D_{9post}	0.0553*	0.0556**	0.0449	0.0528*	0.0452	0.0667**	0.0637**	-0.0039	-0.0039	0.0336	0.0524	0.0110	0.1089	0.0621
D_{10post}	0.0411	0.0455	0.0372	0.0399	0.0532*	0.0005*	0.0505*	0.0432	0.0068	0.0085	0.0208	0.0123	0.0781	0.0068
D_{15post}	0.0459*	0.0433*	0.0405	0.0439	0.0425	0.0410	0.0488*	0.0478	0.0343	0.0089	0.0076	-0.0063	-0.0083	0.0344
D_{20post}	0.0041	0.0102	0.0086	0.0075	0.0082	0.0055	0.0113	0.0329	0.0013	0.0163	0.0206	0.0488	-0.0346	0.0398
D_{24post}	-0.0032	0.0033	-0.0007	-0.0009	0.0052	-0.0201	0.0000	-0.0149	0.0362	0.0024	0.0098	0.0397	-0.0053	0.0275

Table 4. Expiration effect on hourly returns. Continuation

	Expiration of Bakkt bitcoin futures							**Expiration of all bitcoin futures**						
	Binance	Bitfinex	Bitstamp	Coinbase	Gemini	Itbit	Kraken	Binance	Bitfinex	Bitstamp	Coinbase	Gemini	Itbit	Kraken
D_{24}	-0.0695***	-0.0443	-0.0326	-0.0396	-0.0277	-0.0360	-0.0311	-0.0061	-0.0022	0.0065	0.0044	0.0044	0.0025	0.0113
D_{20}	-0.0721*	-0.0665	-0.0170	-0.0683*	-0.0298	-0.0621	-0.0644*	-0.0177	-0.0182	-0.0069	-0.0092	-0.0108	-0.0127	0.0018
D_{15}	-0.0238	0.0188	-0.0037	-0.0200	-0.0195	-0.0100	-0.0116	0.1616***	0.1825***	0.1632***	0.1719***	0.1777***	0.1722***	0.2118***
D_{10}	0.0086	0.0380	0.0509	0.0051	0.0296	0.0080	0.0492	0.0116	0.0073	0.0249	0.0246	0.0258	0.0216	0.0212
D_{9}	0.0363	0.0260	0.0220	0.0141	0.0304	0.0320	0.0425	-0.0033	0.0009	0.0127	0.0110	0.0134	0.0075	0.0115
D_{8}	-0.0027	0.0084	0.0485	-0.0061	0.0227	0.0038	-0.0019	0.0138	0.0174	0.0314*	0.0302*	0.0307*	0.0265	0.0285
D_{7}	0.0092	0.0082	0.0155	0.0117	0.0190	0.0190	-0.0065	0.0022	0.0023	0.0219	0.0208	0.0241	0.0205	0.0177
D_{6}	-0.0005	0.0717	0.0368	0.0694	0.0567	0.0675	0.0124	0.0131	0.0281	0.0292*	0.0201	0.0216	0.0275	0.0227
D_{5}	0.0148	0.0158	0.0155	0.0326	0.0417	0.0631	0.0371	0.0535*	0.067***	0.0791***	0.0699***	0.0771***	0.0739***	0.0686**
D_{4}	0.0375	0.0007	0.0353	-0.0084	0.0020	0.0364	-0.0164	0.0286	0.0292	0.0432	0.0319	0.0419	0.0372	0.0365
D_{3}	0.0165	0.0140	0.0412	0.0022	0.0439	0.0363	0.0269	0.0299	0.0367	0.0475	0.0284	0.0515*	0.0457	0.0471
D_{2}	0.0734	0.0194	0.0944	0.0469	0.0842	0.0961	0.0778	0.1221**	0.1504***	0.1914***	0.1451***	0.1672***	0.1676***	0.1203**
D_{1}	**0.1246**	**0.0926**	**0.0640**	**0.0647**	**0.1051**	**0.0940**	**0.0668**	**0.1616*****	**0.1825*****	**0.1632*****	**0.1719*****	**0.1777*****	**0.1722*****	**0.2118*****
D_{1post}	0.0411	0.0610	0.0584	0.0982	0.0993	0.0408	0.0744	0.1197	0.1417*	0.1643**	0.1433**	0.1379**	0.1363**	0.0490
D_{2post}	-00045	-0.0789	-0.0361	-0.0452	-0.0333	-0.0452	-0.0437	0.0744	0.0032	0.0198	0.0908	0.1483*	0.0934	0.0718
D_{3post}	0.0051	-0.0376	0.0051	0.0253	-0.0292	0.0185	0.0000	0.0054	0.0273	0.0517	0.0194	0.0627	0.0575	0.0861
D_{4post}	0.0077	-0.0266	0.0223	0.0128	0.0085	-0.0068	-0.0005	0.0480	0.0656	0.0576	0.0072	0.0569	0.0532	0.0670
D_{5post}	-0.0042	-0.0197	-0.0360	-0.0012	-0.0018	-0.0041	-0.0075	0.0493	0.0157	0.0428	0.0556	0.0550	0.0455	0.0761
D_{6post}	-0.0549	-0.0579	-0.0561	-0.0438	-0.0621	-0.0398	-0.0625	0.0253	0.0653	0.0063	0.0599	0.0578	0.0690	0.0783
D_{7post}	-0.0577	-0.0503	-0.0662*	-0.0693*	-0.0673*	-0.0375	-0.0733*	0.0400	0.0392	0.0288	0.0349	0.0336	0.0372	0.0371
D_{8post}	-0.0525	-0.0572	-0.0623	-0.0648	-0.0719*	-0.0344	-0.0725**	0.0359	0.0285	0.0205	0.0363	0.0226	0.0372	0.0326
D_{9post}	-0.0054	-0.0038	-0.0143	-0.0196	-0.0160	-0.0102	-0.0241	0.0226	0.0250	0.0218	0.0286	0.0188	0.0258	0.0218
D_{10post}	-0.0458	-0.0471	-0.0558*	-0.0549*	-0.0638**	-0.0425	-0.0714***	0.0143	0.0085	0.0099	0.0122	0.0182	0.0149	0.0196
D_{15post}	-0.0108	-0.0176	-0.0143	-0.0193	-0.0240	0.0079	-0.0283	0.0085	0.0099	0.0335	0.0318	0.0204	0.0095	0.0111
D_{20post}	-0.0204	-0.0277	-0.0178	-0.0214	-0.0283	-0.0083	-0.0301	0.0047	0.0069	0.0126	0.0170	-0.0097	0.0167	0.0058
D_{24post}	-0.0164	-0.0283	-0.0167	-0.0109	-0.0243	-0.0046	-0.0277	0.0041	-0.0153	0.0130	-0.0127	-0.0142	0.0088	-0.0087

Note: This table contains a summary with the coefficients and statistical significance of the variable of interest to test the expiration effect. Coefficients are multiplied by 10^2. All regressions include week-daily dummy variables and dependent lags to adjust autocorrelation. Columns show the results for the different exchanges, Binance, Bitfinex, Bitstamp, Coinbase, Gemini, Itbit and Kraken, respectively. ***, ** and * denote coefficients significant at the 1, 5 and 10 per cent level, respectively.

PART 2: The Witching week of herding on Bitcoin Exchanges

The Witching week of herding on Bitcoin Exchanges

Abstract

This paper analyses the herding behaviour among exchanges around the expiration of bitcoin futures traded on the Chicago Mercantile Exchange (CME). The database extends from December 2017 to October 2020, taking as a reference the main exchanges that trade bitcoin (Binance, Bitfinex, Bitstamp, Coinbase, itBit, Kraken, and Gemini) and using hourly closing prices and trading volumes in bitcoin and US dollars. Adapting the proposal of Chang, Cheng and Khorana (2000) (CCK) to test conditional herding, we obtain results that indicate that the herding effect is significant during the week before expiration. After expiration, the herding effect lasts for a few hours and disappears. Information overload originating, among other causes, from sophisticated investors' strategies may generate this mimetic behaviour. The results show the relevance of intraday data applied to specific events such as expiration since the unconditional analysis shows, in general, anti-herding behaviour throughout the period of study.

1. Introduction

"*Making decisions is like speaking prose - people do it all the time knowingly or unknowingly*"

Kahneman and Tversky, (1984).

Herding is one of the consequences of decision-making. In financial markets, herding occurs when some investors decide to set aside their beliefs and opinions and imitate the decisions of other investors who are thought to be better informed (Scharfstein and Stein, 1990). In a context of bounded rationality, when individuals' private information is overwhelmed by the influence of public information, many investors may tend to follow the market consensus (Devenow and Welch, 1996; Bikhchandani and Sharma, 2001; Hirshleifer and Teoh, 2003, among others, argue along these lines).

The herding effect has been studied from several perspectives (activity sectors, types of investors, analysts, asset characteristics, etc.) and in different markets. Spyrou (2013) offers an interesting survey of papers on herding. In recent years, however, the boom in cryptocurrencies has opened a new field of study regarding this behavioural phenomenon since cryptocurrencies offer a new informational framework that presumably differs from that of more traditional financial markets.

The underlying technology, i.e., blockchain, the information provided by the social networks that are attracting growing interest in these new products, and the information generated within crypto-exchanges themselves allow investors to have an apparently more complete set of information that is not as easily available for other financial products. Corbet et al. (2019) provide a systematic review of the characteristics of cryptocurrencies. Kou et al. (2021a) gather some studies focused on the importance of fintech investment in blockchain systems for sustainable economic development and the simplification and recording of financial operations, among other advantages. Although all these features should contribute to greater informational transparency, both the lack of clear international regulation and the emergence of information overload may undermine such transparency.

The purpose of this paper is to analyse the herding intensity among spot bitcoin exchanges at a very specific moment: around the expiration time of bitcoin futures, when the information flow can noticeably change. The motivation for this study derives from the fact that herding, particularly in the cryptocurrency market, has become a key topic in behavioural finance, as well as the expectations raised by the creation of regulated bitcoin futures in December 2017.

Following the frequently used proposal of Chang, Cheng and Khorana (2000) (CCK), we expand their model to analyse the herding effect around the expiration date of the bitcoin futures contracts traded in the Chicago Mercantile Exchange (CME). That is, we aim to determine whether there is herding behaviour conditioned by the event of expiration. For the analysis, we consider the main bitcoin exchanges worldwide during the period 2018-2020. This paper contributes to the existing literature from both the herding perspective and the cryptocurrency perspective. First, to the best of our knowledge, this study represents the first time that the herding effect has been analysed among exchanges around the futures expiration time. We think that this novelty is valuable since herding among bitcoin exchanges has been studied recently only by Blasco and Corredor (2021). Their analysis was carried out by distinguishing between large and small exchanges and using daily data. In this paper, we use intraday data from the most significant international exchanges. The previous literature highlights the importance of using this data frequency to detect behavioural biases more accurately. Intraday data enable us to find behavioural patterns that can be masked in daily data. The paper analyses imitative behaviour from both the unconditional perspective and the perspective of being conditioned by the specific expiration time, given that there may be differential behaviour by investors before and after the precise expiration time.

Second, this study provides added value to the literature on cryptocurrencies. There have been some studies on herding behaviour among different cryptocurrencies (Bouri, Gupta and Roubaud, 2019; da Gamma Silva et al. 2019; Kallinterakis and Wang, 2019; Stavroyiannis and Babalos, 2019; Vidal-Tomás, Ibañez and Farinos, 2019; Ballis and Drakos, 2020; Kaiser and Stöckl, 2020; Kyriazis, 2020 or Raimundo Júnior et al., 2020) and its relationship with some special events, such as the COVID-19 pandemic (Yarovaya, Matkovskyy and Jalan, 2021) and informative signals

(Philippas et al., 2020). However, none of these studies has focused on herding among exchanges around futures expiration.

Third, we think that our paper contributes to the financial literature on herding in more traditional markets. Although herding behaviour has been detected previously in a number of markets and assets (Chen, 2013, or Chiang and Zheng, 2010, among others), herding on the expiration date has been studied only in some assets traded in the Spanish market (Blasco, Corredor and Ferreruela, 2010). Our current analysis can offer additional knowledge, as it considers different international exchanges trading the same asset, allowing arbitrage strategies in a global market that trades 24/7. These strategies are particularly sought after around the futures expiration times. Under this framework, the herding effect may appear differently from that in more traditional markets and assets. The information flow in the cryptocurrency market may have distinct characteristics that cause peculiar patterns in investors' imitative behaviour.

The rest of the paper is structured as follows: the next section describes the theoretical framework and the working hypotheses; section three describes the database; the fourth section presents the methodology; the fifth and sixth sections contain the results and the robustness analysis; and, finally, the last section summarizes the main conclusions obtained.

2. Theoretical framework and hypotheses

Behavioural finance tries to explain how investors make decisions in a context of bounded rationality, making the efficient market hypothesis compatible with some empirical regularities found in financial markets. Within this framework, herding behaviour has aroused special interest over the last three decades. Among the variety of reasons explaining herding behaviour in financial markets, we note reputation costs (Scharfstein and Stein, 1990, or Trueman, 1994), the activity sector to which a company belongs (Demirer and Zhang, 2018), and even some variables associated with the quality of a specific informational environment (Chang and Lin, 2015 or Blasco, Corredor and Ferreruela, 2017). Nevertheless, investors' reaction to the arrival of information is a common key aspect in all of them. Since the seminal papers by Sheleifer and Summers (1990), Hirshleifer, Subrahmanyam, and Titman (1994) and

Devenow and Welch (1996), mimetic behaviour has been related to either similar reactions of investors to an information set or the lack of quality information. The latter induces contagion in decisions when investors acquire (noisy) information by observing the actions of other agents (Bikhchandani, Hirshleifer, and Welch, 1992, and Welch 1992). More recently, Demirer, Leggio and Lien (2019) suggest a connection between herding and flash events, observing that information in particularly extreme moments with sudden price fluctuations can cause mimetic behaviour. However, as Li et al. (2021) indicate, financial data are social data dominated by multiple complicated latent factors, and they can be affected by changing social environments and time. Therefore, it is difficult to find a catalogue of the circumstances under which herding may appear, which means that herding can be analysed from different perspectives. For example, Zha et al. (2020) review the application of opinion dynamics in finance and business. From the perspective of opinion dynamics, herding can arise if the final evolution of opinion tends towards consensus, which is one of three possible final stable states (alongside polarization and fragmentation).

Herding has traditionally been studied in various markets worldwide, in institutional funds and even among financial analysts. However, interest in this behaviour has recently increased following the emergence of various cryptocurrencies, mainly focusing on price imitation between cryptocurrencies (Bouri, Gupta and Roubaud, 2019; da Gamma Silva et al., 2019; Kallinterakis and Wang, 2019; Stavroyiannis and Babalos, 2019; Vidal-Tomás, Ibañez and Farinos, 2019; Ballis and Drakos, 2020; Kaiser and Stöckl, 2020; Kyriazis, 2020; Philippas et al., 2020; Raimundo Júnior et al., 2020; Yarovaya, Matkovskyy and Jalan, 2021). The information sequences among different cryptocurrencies may have peculiar characteristics compared with stocks, bonds or other currencies, especially due to not only the underlying spirit and technology of this new type of asset but also other spot market indicators such as liquidity, scalability, and the lack of official recognition. All these features can modify the expected reaction of investors. Corbet et al. (2019) summarize the main characteristics of cryptocurrencies and their role as an alternative investment and as a source of diversification while recognizing some correlation between specific markets at specific times.

Although sharing a common base, current cryptocurrencies may show distinct levels of liquidity and generate different degrees of trust among investors. For this reason, for the purpose of this paper, we prefer to focus on a single cryptocurrency, bitcoin, which represented approximately 75% of the market capitalization of the 10 top cryptocurrencies in January 2021[10]. By doing so, we intend to isolate our results from other effects that can be associated with other cryptocurrencies with their own characteristics.

Similar to the opening and closing of any trading session, the expiration date has been identified as an information-revealing time. Spot markets that have an associated derivatives market are supposed to be more complete since they enable a wider range of arbitrage and hedging strategies, even price manipulation. On the expiration date, investors must decide about their market position, either closing and settling, rebalancing or rolling over, based on their information and expectations. In fact, the so-called witching hour (the last hour of trading when options and futures contracts expire) is often characterized by heavy volumes as traders close out or roll their positions before expiry. In turn, such decisions generate new information. Furthermore, some authors, such as Kumar and Seppi (1992), point out that price manipulation is more intense around expiration dates, which leads to uncertainty and increases risk. All these extra information flows revealing sophisticated investors' strategies, added to the habitual information sets that also affect non-expiration dates, can noticeably foster mimetic behaviour among investors. The effects of these informational changes on market variables such as returns, volume and volatility have been studied in depth (Stoll and Whaley (1987 and 1991) or Alkbäkc and Hagelin (2004), among others), but it seems to be clear that this information flow could affect investors' reactions and, in particular, their mimetic behaviour when making their decisions. To date, however, this approach has been little studied.

Cryptocurrency markets are not exempt from these effects on futures expiration dates. Since December 2017, when the Chicago Board Options Exchange (CBOE) and CME started trading regulated bitcoin futures, investors have shown active

[10] The data are provided by the CME Group and coinmarketcap.com

involvement in this market[11], and therefore, their strategies may have induced herding effects in the bitcoin spot market around expiration dates. In light of these arguments, we propose to test the following working hypotheses:

Hypothesis 1: There is a herding effect among bitcoin exchanges before the bitcoin futures expiration date.

Hypothesis 2: If it exists, herding disappears after the futures expiration date.

Figure 1 shows a flow chart with the main steps of the analysis and the procedures that we followed, including some robustness tests.

3. Database

Bitcoin futures contracts traded in regulated markets began their journey in December 2017. Within only one week of each other, the CBOE and the CME launched their respective futures contracts (on 10 and 17 December, respectively), although the CBOE stopped trading bitcoin futures in summer 2019. Shortly thereafter, in September 2019, the Intercontinental Exchange (ICE) introduced a new bitcoin futures contract traded on the Bakkt platform.

To consider the largest possible number of observations, we focus on the futures contracts offered by the CME, which remained uniform during the period of analysis and registered the highest volume of all three regulated markets. The expiration time of this futures contract takes place on the last Friday of each month at 4:00 p.m. London time, and the settlement price is based on the Bitcoin Reference Rate (BRR) calculated by the CME. The BRR is a daily reference index that aggregates the bitcoin quotes of major spot exchanges to ensure credibility. These constituent exchanges are Bitstamp, Coinbase, itBit and Kraken (since December 2017) as well as Gemini (since 30 August 2019). The contract unit (contract

[11] As of 20 May 2021, Arcane Research reports a new trading record ($200B) considering regulated and unregulated bitcoin futures contracts.

multiplier) is 5 bitcoins, the price quotation is expressed in US dollars and cents per bitcoin, and the settlement method is cash settlement.

For the purpose of this paper, we take hourly bitcoin prices from seven reference exchanges. Specifically, Bitstamp, Coinbase, itBit, Kraken and Gemini, the constituent exchanges of the CME, are chosen because they provide information that can be applied to compute the price of the underlying asset in CME bitcoin futures. We also include Binance and Bitfinex since they are clear references in terms of trading volume. All of these exchanges are usually among the top 10% of bitcoin exchanges.

The data source is http://www.cryptodatadownload.com, which offers hourly closing prices and trading volumes in bitcoin and US dollars. Unix Timestamp is taken to unify the time information of all the markets under analysis, as it is based on UTC, is nearly monotonic, and is easier to parse and use across different operating systems and file formats. Daylight savings time is also considered when the Unix Timestamp is converted into human-readable local time.

Given that the aim of this paper is to analyse herding among exchanges around expiration dates and given that bitcoin futures contracts started in December 2017, our database extends from December 2017 to October 2020[12].

Table 1 shows some descriptive statistics of the bitcoin exchanges[13]. Binance is by far the largest exchange, considering the trading volume of the different cryptocurrencies, derivatives, stable coins and tokens globally traded, followed by Coinbase, Kraken, Bitfinex and Bitstamp. In our sample, Gemini and itBit are the smallest exchanges. However, regarding bitcoin trading exclusively, Binance and Bitfinex are the most noteworthy exchanges by volume, followed by Coinbase and Bitstamp. Furthermore, the CME-constituent exchanges hold the highest scores on

[12] The end of the period is driven by the data availability in http://www.cryptodatadownload.com.

[13] The global trading volume is the average of the information provided by https://www.cryptocompare.com/exchanges/#/overview and https://coinmarketcap.com/es/rankings/exchanges/ on 14 June 2021 and includes all assets traded.
The T-S Score represents the sum (over 100) of some category items such as regulation, data provision, security, trade monitoring and the negative reports provided by CryptoCompare (https://www.cryptocompare.com/exchanges/#/overview, June 14th 2021).

transparency and security items, proving to be valuable for the purpose of CME price calculation. Finally, the geographical distribution of the headquarters and registration offices of all the exchanges analysed, as well as the geographical distribution of their electronic platforms and services, allow worldwide coverage of bitcoin trading, which is also valuable for the robustness of our results.

4. Methodology

4.1. Unconditional herding behaviour

One of the approaches commonly used to detect mimetic behaviour is the CCK model. This model tests the nonlinear relationship between the cross-sectional dispersion of asset returns and market returns. Herding is detected when this relationship is significantly negative. We adopt and adapt this proposal considering the cross-sectional dispersion of the prices provided by the seven exchanges under analysis and their weighted market returns. The weighting process is initially carried out by bitcoin volume.

The initial model is as follows:

$$CSAD_t = \gamma_0 + \gamma_1 |Rm_t| + \gamma_2 Rm_t^2 + \varepsilon_t \quad (1)$$

where $CSAD_t$ represents the cross-sectional absolute deviation of bitcoin returns among the exchanges included in our sample at hour t. It is calculated as follows:

$$CSAD_t = \frac{\sum_1^n |R_{it} - Rm_t|}{n} \quad (2)$$

where R_{it} is the hourly return of bitcoin in exchange i and R_{mt} is the hourly weighted return index of bitcoin prices. Notably, the calculation of this market return involves a subjective component, given that there is no other hourly reference index during the time horizon of the analysis. Nevertheless, as the exchanges considered are representative of the global market, we think that the market index is appropriate for our purposes. The model also includes five lags of the cross-sectional absolute deviation (CSAD) to correct for autocorrelation[14]. The omission of relevant variables could cause the herding coefficients to be falsely significant and therefore lead to misleading results. Correcting for autocorrelation prevents herding, if detected, from being attributed to omitted variables. We adopt the ordinary least squares (OLS) procedure of estimation using Newey–West heteroskedasticity and autocorrelation consistent (HAC) covariance estimators.

The test is based on the assumption that in the presence of herding, a large movement of market returns will induce a nonlinear reduction in the CSAD measure if the exchanges involved mimic one another. Such a reaction will be reflected in a significantly negative γ_2 coefficient.

4.2. Herding behaviour conditioned by the expiration time

To test herding behaviour around expiration times, we extend the model by following the proposal of Zhou and Anderson (2013). In this extension, the model is conditioned by the specific event of bitcoin futures expiration. We include in the model a dummy variable D_{exp}, which identifies a particular time interval associated with the expiration time. The structure of the model is described as follows:

$$CSAD_t = \gamma_0 + \gamma_1 D_{\exp}\left|Rm_t\right| + \gamma_2 (1 - D_{\exp})\left|Rm_t\right| + \gamma_3 D_{\exp} Rm_t^2 + \gamma_4 (1 - D_{\exp}) Rm_t^2 + \varepsilon_t \qquad (3)$$

where variable D_{exp} is defined differently in each estimation and varies to reveal the temporal evolution before and after the expiration time according to the suggestions in Corredor, Lechon and Santamaria (2001) for computing cumulative effects. Thus, D_{exp} is substituted by D_0, D_{1pre}, D_{2pre}, …D_{24pre} and D_{1post}, D_{2post}…D_{24post} alternatively in each regression. D_0 takes the value of 1 for the hour of expiration and 0 otherwise, D_{1pre} takes the value of 1 both for the hour of expiration and one hour beforehand and

[14] To avoid the serial autocorrelation detected, the number of lags is jointly determined by their significance (lags 6 and 7 were not significant), the closest-to-2 values of the Durbin–Watson (DW) statistic and the minimum values of the Akaike information criterion (AIC).

0 otherwise and so on until D_{24pre}, which identifies the hour of expiration and 24 hours beforehand. Similarly, we create dummy variables for after futures maturity, from D_{1post}, which takes the value of 1 for one hour after expiration and 0 otherwise, to D_{24post}, which takes the value of 1 for up to 24 hours after expiration and 0 otherwise. These variables capture the effect under analysis 24 hours before and after futures maturity (which may even correspond to different dates depending on the time zones).

Furthermore, very intense informational flows around the expiration week have been detected, and these flows can cause significant changes in some trading measures in more traditional markets (see, among others, the classic works of Stoll and Whaley (1987 and 1991) and Alkbäkc and Hagelin (2004), who summarize the main studies on this subject). This evidence suggests that the expiration effect might be extended to longer-than-one-day periods. In fact, the previously mentioned concept of the "witching hour" can be extended to the so-called "quadruple witching hour" if the maturities of several derivatives coincide. The "quadruple witching hour" is often linked to abnormal volumes and returns on the days around expiration. In the bitcoin market, there is a range of different futures contracts, both regulated and unregulated, and many of them have an expiration date close to the expiration of the CME futures contract, which we identify as the most relevant. The possibility of a "multiple witching hour" could make changes in investor behaviour last more than one day.

Taking into account these circumstances, we also create additional dummy variables for up to 150 hours before and after the expiration time. These additional variables are intended to detect the possible herding effect approximately 5 days before and after expiration (more or less one working week before expiration, as expiration takes place on the last Friday of the month, and until halfway through the week after expiration, which includes the following weekend and three working days).

To detect herding around futures expiration, the γ_3 estimates should be negative and significant. γ_4 reflects the herding effect, if any, in periods not identified as expiration times. The estimation procedure involves 300 OLS regressions using Newey–West HAC covariance estimators.

5. Empirical results

Table 2 shows the results of the unconditional hourly herding estimates. The coefficient associated with herding is significant and positive; therefore, we do not find evidence of herding when the global period is analysed without considering the specific expiration event. This result is consistent with the findings of Blasco and Corredor (2021) for large exchanges using daily data. In light of these first no-herding (in fact anti-herding) results, confirmed using intraday data and evidencing that investors generally react independently without following the market consensus, we think that it is interesting to take one step forward and test whether investors change their reactions and herd around the specific event of futures expiration with intraday data, which can be more revealing.

Table 3 offers a summary overview of the results of the 150 estimates performed, including in the model the dummy variables related to the range of periods before the expiration time and at the expiration time itself. Each row contains the estimated parameters of the model for one dummy variable associated with the expiration time (D_0, D_{1pre}…or D_{150pre}). The table shows detailed information for the nearest hours before expiration and a summary every 12 hours until the farthest moments.

The results indicate that at both the expiration time and one hour before, there is no significant herding effect. Nevertheless, this effect is significantly noticeable from two hours before maturity, and it extends not only up to 24 hours (one day) before expiration but also up to 137 hours before maturity, before which the herding parameter is no longer significant. This change in significance can be appreciated by comparing the D_{132pre} and D_{144pre} results.

According to these results, Hypothesis 1 can be confirmed since our findings reveal a significant herding effect in the working week prior to the expiration time. Informational changes around expiration induce changes in investors' behaviour, as their reaction goes from making decisions on their own to imitating each other, probably due to the uncertainty generated around expiration by the information overload hampering investors' decision-making. Herding may seem to be a suitable alternative for making apparently informed decisions when investors cannot manage the informational excess.

Table 4 shows the same type of information but, in this case, for dummy variables associated with a number of hours after futures expiration. The results indicate that there is no herding effect in the nearest hours after expiration. However, herding appears from 7 hours up to 12 hours after expiration, probably because investors actively re-open new positions and generate a new, albeit briefer, informational excess that encourages mimetic behaviour. From that time, in line with the results for non-expiration days and the unconditional results, herding disappears. The joint reading of the results indicates that the herding effect starts decreasing 13 hours after expiration and subsequently turns into anti-herding behaviour.

These results confirm Hypothesis 2. Although some herding appears after expiration, it does not last for long and supposedly gives rise to the anti-herding reaction that basically holds until the next expiration week.

Taken together, the results lead us to conclude that there exists a differential reaction of investors around bitcoin futures expiration as opposed to non-expiration times.

Figure 2 shows how the significant herding coefficients obtained with the regression procedure evolve over time. When bitcoin futures contracts are coming to an end, investors who trade in different exchanges mimic each other. This herding behaviour also occurs a few hours after expiration, probably due to the readjustment of strategies that takes place after expiration and the re-opening of contracts that will expire at a later date. Outside of the hours close to expiration, investors do not significantly imitate each other. In fact, we generally observe a clear anti-herding behaviour.

Regarding the concept of the witching hour, the trading volume of the exchanges that belong to our sample grows by approximately 2% at the beginning of the expiration week, reaching an increase of approximately 5.5% in the 24 hours prior to expiration. These increases are corrected, at a similar pace, after expiration. The volume increases prior to expiration are consistent with the excess of information at those times (and, therefore, with the difficulty of processing it) and with the incentive of herding practices that disappear after maturity.

6. Robustness analyses

The results reported above come from model estimations using a market index return weighted by bitcoin volume. To ensure the robustness of the results, the models are re-estimated using a market return calculated as an index weighted by the US volume of traded bitcoins. Table 5 shows a summary of the coefficients strictly associated with herding behaviour conditioned by the expiration time. These results are similar to those previously described, which allows us to confirm that the results do not depend on the index considered as the market reference.

To provide additional alternative estimates not based on the mean, we use the quantile regression procedure. This methodology allows the model to be estimated in different quantiles of a distribution. We use the 50th quantile of the conditional distribution of the CSAD, which is representative of the median of the distribution. Table 6 lists the main coefficients for the bitcoin volume weighted index[15]. The results obtained allow us to confirm the previous findings since the herding effect is observed in the hours before expiration, although it starts slightly later (approximately 112 hours before expiration) than when using other regression methods. The herding effect after expiration occurs during a shorter period and then, consistent with our previous findings, gives rise to significant anti-herding behaviour.

Finally, we also conduct a specific robustness analysis using one of the frequently referenced proposals in the financial literature: the seminal model by Christie and Huang (1995) (CH). The CH model tests the linear relationship between the dispersion of returns and extreme market returns and detects herding under extreme market movements. An initial analysis of our sample indicates that approximately 98.7% of the 1% extreme positive returns and the 1% extreme negative

[15] The results using the US volume weighted index are similar and are available upon request from the authors.

returns of our period of analysis fall within non-expiration periods. This result means that the CH model is not the best method for detecting herding around the expiration time. Nevertheless, the CH model may be useful for testing what happens outside expiration times and, in particular, for checking the anti-herding behaviour detected on non-expiration days as well as the significantly positive linear relationships shown in the first two columns of Tables 3 and 4 using the CCK model.

Table 7 summarizes the main results. The first two rows present the result of the average estimates and the significance of the variables included in the model around expiration times and at non-expiration times. As expected, the anti-herding behaviour on non-expiration days is clearly detected, as is a positive linear relationship between dispersion measures and market returns, although this relationship is not strictly significant at the usual 10% confidence level. Compared with the first two columns of Tables 3 and 4, which are based on the CCK model, we think that the results differ for two reasons: first, because the linear relationship in the CCK model considers both extreme and non-extreme market returns and, second, because of the possibility of herding at very specific periods with extreme returns. For this reason, we also include in the table (third and fourth rows) the average estimates (and average significance levels) corresponding to the expiration variables D_{4pre} to D_{8pre} and D_{8post} to D_{11post}. On the one hand, consistent with our initial findings, with the CH model, we detect herding starting 8 hours before expiration until 4 hours before expiration in the case of the lowest market returns. On the other hand, we find negative coefficients, although not significant, during the same post-expiration hours as in the CCK model. Once again, it is important to remember that the CH model detects herding only at times of extreme returns. These returns seldom occur around futures maturity times.

In summary, the CH model supports our previous findings confirming the anti-herding behaviour on non-expiration days and the noticeable linear relationship between dispersion measures and extreme market returns. It even suggests the relevance of the herding effect some hours prior to the expiration time when extreme negative returns appear. Hence, bearing in mind the differences between the CH and CCK models, we conclude that the findings of the CH test are consistent with our initial results.

In this robustness analysis, we used some of the common approaches to detect herding. However, some authors have recently proposed analytical tools using models coming from physics and mathematics to address financial issues. Kou et al. (2014) and Li et al. (2021) show the usefulness of some multi-criteria decision-making (MCDM) methods and adaptive algorithms for evaluating clustering algorithms and detecting clusters in financial data. In the same vein, Kou et al. (2021a) use fuzzy methodology, and Kou et al. (2021b) propose multi-objective optimization. Zha et al. (2020) indicate that some binary opinion dynamics models could help in understanding the decision-making process. As a social phenomenon, herding behaviour can be affected by multiple latent factors. In the future, research on this behaviour could also be framed as a multi-criteria and/or clustering problem around an event.

7. Conclusions

The purpose of this paper is to test the herding effect among bitcoin exchanges around the expiration date of bitcoin futures. The emergence of bitcoin futures contracts in regulated markets offers a unique opportunity to analyse the mimetic behaviour of investors more closely. Bitcoin futures have attracted interest from institutional investors who consider this new asset an additional investment opportunity. This interest helps to increase the liquidity of the spot market and leads to the appearance of sophisticated investors in Bitcoin markets. If these investors seek to take advantage of the expiration time in their speculative or arbitrage strategies, less informed investors will probably monitor and imitate their movements.

Using intraday data and an unconditional model, we confirm, on average, anti-herding behaviour for the period. However, our results go one step further by showing that at certain moments, in which the discovery of strategies and information overload are key features, herding may appear if investors find difficulties in processing information to generate their expectations. Consistent with our hypotheses, we find a strong herding effect before expiration and a few hours after expiration. Specifically, these effects extend throughout the week prior to expiration and disappear quickly the day after expiration.

The results suggest that bitcoin prices generally reflect investors' own information, but particularly in the week of bitcoin futures expiration, this point is questionable since investors seem to watch each other closely. If the herding effect is evident during the expiration week, the information flow may not be as informative and could be contaminated.

The herding effect should be studied in detail since, as our findings indicate, it is not homogeneous at all times. The influence of important factors such as fear of missing out (FOMO), confirmation bias and overconfidence (see, among others, Merkle and Weber (2011) or Baur and Dimpfl (2018)) on the psychology of investors that causes the decision to herd means that herding is important enough to be analysed conditioned by the occurrence of different events and in various markets. In addition, the strong growth in bitcoin trading is itself the result of psychological factors that make this analysis even more interesting. Furthermore, as Corbet et al. (2019) point out, there must be ongoing research on cryptocurrencies since their behaviour is continually changing.

In general, the direct consequences of herding for financial investors occur in two ways. On the one hand, herding makes it more difficult to diversify investment portfolios, and on the other hand, financial assets may be mispriced due to price pressures that increase volatility and market instability and that can therefore drive prices away from their expected values. In our paper, the first consequence does not have great implications for relevant investors since we analyse the herding that occurs between exchanges that trade the same asset, bitcoin, and, presumably, their diversification strategies mainly focus on different assets instead of the same asset in different markets or on different platforms. However, mispricing can affect all investors in all exchanges at maturity times, with the exception of bitcoin holders (hodlers), whose objective is long-term gains.

Around maturity time, investors are aware of the number of informational elements that may influence decision-making. For this reason, many uninformed investors may find it useful to imitate the decisions of others, transferring that imitation to the different exchanges where bitcoin is traded. Herding between exchanges can amplify the mispricing of bitcoin since imitation spreads throughout different markets and platforms. Consequently, market players will not be able to adequately predict prices and may find volatility levels that intensify the risk assumed. In volatile markets such as crypto markets and at times of volatility, price slippages tend to occur. Therefore, at the time of executing a transaction during herding periods, asset prices can shift noticeably before the transaction is completed. Hence, exchanges should ensure that liquidity providers such as market makers (makers) and liquidity pools create multiple bid-ask orders to match the orders (especially large orders) of other traders to execute transactions instantaneously and to reduce price slippages.

More specifically, our results also have implications for investors who design their strategies encompassing several exchanges since they must take into account that price differentials narrow in the hours close to expiration. Consequently, market participants who act as arbitrageurs or hedgers betting on different exchanges in bitcoin will have more limited possibilities of obtaining profits. Arbitrage traders who participate in triangular arbitrage trading (which involves spotting the price differences between three different cryptocurrencies, even on the same exchange) should review their strategies involving bitcoin, while hedging and arbitrage investors operating in both the spot and futures markets should review their hedge ratios.

Policy makers should also realize that the expiration week is an atypical week in which exchanges tend to follow the market consensus. This behaviour could be worrying in the case of large market fluctuations when the risk associated with feelings of pessimism or euphoria could spread to all exchanges.

In financial markets, decision-making is a significant issue. Herding is a consequence of decision-making, which is why it is interesting to understand it from different perspectives. In the future, to further investigate investors' behaviour in financial markets, as Zha et al. (2020) suggest, it will be necessary to conduct integrated in-depth interdisciplinary research.

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Table 1. Descriptives of Exchanges

Name	**Country/Region**	**Global trading volume**	**T-S Score**	**Bitcoin trading volume**	
		USD		BTC	USD
Binance	Malta (started in China)	19.96 B	70.25	46,043.67	390.84 M
Bitfinex	Hong Kong and British Virgin Islands	730.63 M	71.57	18,103.00	144.84 M
Bitstamp	Luxembourg and U.K.	516.52 M	80.54	9,235.25	76.43 M
Coinbase	U.S.A	2.34 B	85.31	13,157.30	111.54 M
Gemini	U.S.A	185.47 M	82.87	3,032.04	24.51 M
itBit	U.S.A	17.24 M	75.60	2,090.58	14.67 M
Kraken	U.S.A	1.33 B	75.86	6,277.87	50.54 M

Global trading volume (USD) includes the daily trading volume of all cryptocurrencies in the exchange. Bitcoin trading volume shows mean daily bitcoin trading volume for the period under analysis in BTC and USD. T-S Score shows the score of transparency and security of the exchanges.

Table 2. Unconditional hourly herding

	Intercept	**|Rm|**	**Rm^2**	**R-Squared**
Coefficient	0.000094***	0.022284***	0.119712***	0.51
p-value	*0.00*	*0.00*	*0.00*	

The table shows the estimates of the following model: $CSAD_t = \gamma_0 + \gamma_1 |Rm_t| + \gamma_2 Rm_t^2 + \varepsilon_t$ Estimation includes five lags of CSAD. Results using Newey-West heteroscedasticity and autocorrelation consistent estimators. ***, **, * indicate significance at 1%, 5% and 10% respectively.

Table 3. Conditional hourly herding around the expiration. *Effects before expiration*

	$\lvert Rm\rvert D_{exp}$	*p-value*	$\lvert Rm\rvert (1-D_{exp})$	*p-value*	$Rm^2 Dexp$	*p-value*	$Rm^2 (1-D_{exp})$	*p-value*
D_{0pre}	0.008933	*0.38*	0.022401***	*0.00*	-0.057812	*0.66*	0.120766***	*0.00*
D_{1pre}	0.024648**	*0.03*	0.022420***	*0.00*	-0.252231	*0.12*	0.121037***	*0.00*
D_{2pre}	0.024000***	*0.00*	0.022430***	*0.00*	-0.243977**	*0.04*	0.120966***	*0.00*
D_{3pre}	0.018397***	*0.00*	0.022483***	*0.00*	-0.172351*	*0.09*	0.120649***	*0.00*
D_{4pre}	0.016822***	*0.00*	0.022500***	*0.00*	-0.146958*	*0.10*	0.120484***	*0.00*
D_{5pre}	0.019882***	*0.00*	0.022492***	*0.00*	-0.191643**	*0.03*	0.120556***	*0.00*
D_{6pre}	0.018545***	*0.00*	0.022535***	*0.00*	-0.187597**	*0.02*	0.120374***	*0.00*
D_{7pre}	0.018927***	*0.00*	0.022567***	*0.00*	-0.200714**	*0.01*	0.120217***	*0.00*
D_{8pre}	0.022140***	*0.00*	0.022542***	*0.00*	-0.241857***	*0.00*	0.120390***	*0.00*
D_{9pre}	0.024896***	*0.00*	0.022526***	*0.00*	-0.282716***	*0.00*	0.120546***	*0.00*
D_{10pre}	0.024738***	*0.00*	0.022528***	*0.00*	-0.279675***	*0.00*	0.120526***	*0.00*
D_{11pre}	0.023111***	*0.00*	0.022568***	*0.00*	-0.258277***	*0.00*	0.120264***	*0.00*
D_{12pre}	0.022020***	*0.00*	0.022582***	*0.00*	-0.239787***	*0.00*	0.120124***	*0.00*
D_{24pre}	0.025626***	*0.00*	0.022651***	*0.00*	-0.218656**	*0.02*	0.120094***	*0.00*
D_{36pre}	0.023554***	*0.00*	0.022903***	*0.00*	-0.210605**	*0.02*	0.118640***	*0.00*
D_{48pre}	0.022224***	*0.00*	0.023259***	*0.00*	-0.198201***	*0.00*	0.119003***	*0.00*
D_{60pre}	0.023577***	*0.00*	0.023463***	*0.00*	-0.218285***	*0.00*	0.118233***	*0.00*
D_{72pre}	0.022907***	*0.00*	0.023513***	*0.00*	-0.165259***	*0.00*	0.120910***	*0.00*
D_{84pre}	0.022228***	*0.00*	0.023666***	*0.00*	-0.153775***	*0.00*	0.119602***	*0.00*
D_{96pre}	0.021132***	*0.00*	0.024086***	*0.00*	-0.139471***	*0.00*	0.116873***	*0.00*
D_{108pre}	0.021542***	*0.00*	0.024208***	*0.00*	-0.134961***	*0.00*	0.118085***	*0.00*
D_{120pre}	0.021739***	*0.00*	0.024560***	*0.00*	-0.134089***	*0.00*	0.117738***	*0.00*
D_{132pre}	0.022085***	*0.00*	0.024600***	*0.00*	-0.129278***	*0.00*	0.117071***	*0.00*
D_{144pre}	0.020183***	*0.00*	0.024257***	*0.00*	-0.009304	*0.94*	0.115029***	*0.00*
D_{150pre}	0.020410***	*0.00*	0.024261***	*0.00*	-0.013052	*0.92*	0.115047***	*0.00*

The table shows the estimates of Equation (3) including five lags of CSAD.

$$CSAD_t = \gamma_0 + \gamma_1 D_{\exp}\lvert Rm_t\rvert + \gamma_2(1-D_{\exp})\lvert Rm_t\rvert + \gamma_3 D_{\exp} Rm_t^2 + \gamma_4(1-D_{\exp})Rm_t^2 + \varepsilon_t$$

D_{exp} is the dummy variable, defined differently, that takes value 1 in specific times around expiration and 0 otherwise. Each raw contains the estimated parameters of the model for one dummy variable associated to D_{exp}. For example, D_{0pre} is the dummy variable that takes value 1 at the expiration hour and 0 otherwise; the dummy variable D_{1pre} takes a value of 1 both at the hour of expiration and one hour beforehand and 0 otherwise; the dummy variable D_{2pre} takes a value of 1 at the hour of expiration and 2 hours beforehand and 0 otherwise and so on, until D_{150pre} takes a value of 1 at the hour of expiration and 150 hours beforehand and 0 otherwise. Results using Newey-West heteroscedasticity and autocorrelation consistent estimators. ***, **, * indicate significance at 1%, 5% and 10% respectively.

Table 4. Conditional hourly herding around the expiration. *Effects after expiration*

	|Rm| D_{exp}	*p-value*	**|Rm| (1-D_{exp})**	*p-value*	**Rm^2 D_{exp}**	*p-value*	**Rm^2 (1-D_{exp})**	*p-value*
D_{1post}	0.012322	*0.68*	0.022285***	*0.00*	0.418478	*0.84*	0.119694***	*0.00*
D_{2post}	0.021159	*0.20*	0.022292***	*0.00*	-0.734098	*0.57*	0.119624***	*0.00*
D_{3post}	0.026065*	*0.06*	0.022308***	*0.00*	-1.355730	*0.18*	0.119485***	*0.00*
D_{4post}	0.028366	*0.00*	0.022313***	*0.00*	-0.637224**	*0.01*	0.119528***	*0.00*
D_{5post}	0.010699	*0.42*	0.022175***	*0.00*	1.724394	*0.25*	0.120379***	*0.00*
D_{6post}	0.007434	*0.60*	0.022172***	*0.00*	1.638034	*0.25*	0.120386***	*0.00*
D_{7post}	0.039646	*0.00*	0.022354***	*0.00*	-0.588967**	*0.01*	0.119911***	*0.00*
D_{8post}	0.040108***	*0.00*	0.022342***	*0.00*	-0.591755**	*0.01*	0.120019***	*0.00*
D_{9post}	0.043976***	*0.00*	0.022336***	*0.00*	-0.564799***	*0.00*	0.120599***	*0.00*
D_{10post}	0.037778***	*0.00*	0.022282***	*0.00*	-0.285752**	*0.04*	0.122907***	*0.00*
D_{11post}	0.035776***	*0.00*	0.022309***	*0.00*	-0.265037**	*0.05*	0.122797***	*0.00*
D_{12post}	0.033322***	*0.00*	0.022336***	*0.00*	-0.231733*	*0.06*	0.122568***	*0.00*
D_{24post}	0.044162***	*0.00*	0.021857***	*0.00*	-0.201611	*0.34*	0.123800***	*0.00*
D_{36post}	0.030587***	*0.00*	0.022035***	*0.00*	-0.005767	*0.97*	0.122074***	*0.00*
D_{48post}	0.030284***	*0.00*	0.022165***	*0.00*	-0.073014	*0.54*	0.123255***	*0.00*
D_{60post}	0.028028***	*0.00*	0.022224***	*0.00*	-0.039580	*0.74*	0.122706***	*0.00*
D_{72post}	0.026360***	*0.00*	0.022313***	*0.00*	-0.023231	*0.85*	0.122173***	*0.00*
D_{84post}	0.015260***	*0.03*	0.022182***	*0.00*	0.381875	*0.16*	0.110753***	*0.00*
D_{96post}	0.015689***	*0.03*	0.022224***	*0.00*	0.346543	*0.20*	0.111515***	*0.00*
$D_{108post}$	0.015253***	*0.03*	0.022297***	*0.00*	0.349972	*0.19*	0.110961***	*0.00*
$D_{120post}$	0.014833***	*0.02*	0.022386***	*0.00*	0.353606	*0.18*	0.110248***	*0.00*
$D_{132post}$	0.014554***	*0.02*	0.022519***	*0.00*	0.346307	*0.18*	0.109699***	*0.00*
$D_{144post}$	0.013743***	*0.03*	0.022783***	*0.00*	0.344795	*0.18*	0.108177***	*0.00*
$D_{150post}$	0.013665***	*0.03*	0.022873***	*0.00*	0.340398	*0.18*	0.107759***	*0.00*

The table shows the estimates of Equation (3) including five lags of CSAD.

$$CSAD_t = \gamma_0 + \gamma_1 D_{\exp}|Rm_t| + \gamma_2(1-D_{\exp})|Rm_t| + \gamma_3 D_{\exp} Rm_t^2 + \gamma_4(1-D_{\exp})Rm_t^2 + \varepsilon_t$$

D_{exp} is the dummy variable, defined differently, that takes value 1 in specific times around expiration and 0 otherwise. Each raw contains the estimated parameters of the model for one dummy variable associated to D_{exp}. For example, the dummy variable D_{1post} takes a value of 1 one hour after expiration and 0 otherwise; the dummy variable D_{2post} takes a value of 1 two hours after expiration and 0 otherwise and so on, until $D_{150post}$ which takes a value of 1 150 hours after expiration and 0 otherwise. Results using Newey-West heteroscedasticity and autocorrelation consistent estimators. ***, **, * indicate significance at 1%, 5% and 10% respectively

Table 5. Robustness tests OLS regressions using the US volume to compute the return of the market index

	Before expiration				After expiration			
	Rm^2 D_{exp}	***p-value***	**Rm^2 (1-D_{exp})**	***p-value***	**Rm^2 D_{exp}**	***p-value***	**Rm^2 (1-D_{exp})**	***p-value***
D_0	-0.053979	*0.67*	0.130189***	*0.00*				
D_1	-0.250259	*0.11*	0.130464***	*0.00*	0.388974	*0.85*	0.129033***	*0.00*
D_2	-0.250472**	*0.03*	0.130403***	*0.00*	-0.769407	*0.57*	0.128967***	*0.00*
D_3	-0.176641*	*0.08*	0.130074***	*0.00*	-1.432647	*0.17*	0.128811***	*0.00*
D_4	-0.148310*	*0.10*	0.129895***	*0.00*	-0.643818**	*0.01*	0.128847***	*0.00*
D_5	-0.194445**	*0.03*	0.129967***	*0.00*	1.680901	*0.26*	0.129735***	*0.00*
D_6	-0.191027**	*0.02*	0.129779***	*0.00*	1.579844	*0.27*	0.129743***	*0.00*
D_7	-0.209440**	*0.01*	0.129641***	*0.00*	-0.616743**	*0.01*	0.12927***	*0.00*
D_8	-0.251632***	*0.00*	0.129823***	*0.00*	-0.613975**	*0.01*	0.129371***	*0.00*
D_9	-0.293610***	*0.00*	0.129984***	*0.00*	-0.580343***	*0.00*	0.129977***	*0.00*
D_{10}	-0.289650***	*0.00*	0.129958***	*0.00*	-0.287979**	*0.05*	0.132318***	*0.00*
D_{11}	-0.269501***	*0.00*	0.129698***	*0.00*	-0.266867*	*0.06*	0.132208***	*0.00*
D_{12}	-0.250075***	*0.00*	0.12955***	*0.00*	-0.23315*	*0.07*	0.131977***	*0.00*
D_{24}	-0.217145**	*0.02*	0.129434***	*0.00*	-0.223279	*0.34*	0.133618***	*0.00*
D_{36}	-0.210673**	*0.02*	0.127982***	*0.00*	-0.003387	*0.98*	0.131698***	*0.00*
D_{48}	-0.200823***	*0.00*	0.128431***	*0.00*	-0.07922	*0.52*	0.133018***	*0.00*
D_{60}	-0.222531***	*0.00*	0.127654***	*0.00*	-0.041301	*0.74*	0.132417***	*0.00*
D_{72}	-0.168169***	*0.00*	0.130481***	*0.00*	-0.024072	*0.85*	0.13192***	*0.00*
D_{84}	-0.156841***	*0.00*	0.129151***	*0.00*	0.395257	*0.16*	0.120234***	*0.00*
D_{96}	-0.142887***	*0.00*	0.126423***	*0.00*	0.370497	*0.19*	0.120421***	*0.00*
D_{108}	-0.139415***	*0.00*	0.127735***	*0.00*	0.373491	*0.18*	0.119851***	*0.00*
D_{120}	-0.141292***	*0.00*	0.127462***	*0.00*	0.376754	*0.17*	0.119123***	*0.00*
D_{132}	-0.139337***	*0.00*	0.126884***	*0.00*	0.36893	*0.17*	0.118529***	*0.00*
D_{144}	-0.015067	*0.90*	0.124704***	*0.00*	0.366243	*0.17*	0.116988***	*0.00*
D_{150}	-0.018918	*0.88*	0.124733***	*0.00*	0.361358	*0.17*	0.116555***	*0.00*

The table shows the estimates of Equation (3) including five lags of CSAD.

$$CSAD_t = \gamma_0 + \gamma_1 D_{\exp}\left|Rm_t\right| + \gamma_2(1-D_{\exp})\left|Rm_t\right| + \gamma_3 D_{\exp} Rm_t^2 + \gamma_4(1-D_{\exp})Rm_t^2 + \varepsilon_t$$

D_{exp} is the dummy variable, defined differently, that takes value 1 in specific times around expiration and 0 otherwise. Each raw contains the estimated parameters of the model for one dummy variable associated to D_{exp}. For example, the dummy variable D_1 takes a value of 1 one hour before (after) expiration and 0 otherwise; the dummy variable D_2 takes a value of 1 2 hours before (after) expiration and 0 otherwise and so on, until D_{150} that takes a value of 1 150 hours before (after) expiration and 0 otherwise. Results using Newey-West heteroscedasticity and autocorrelation consistent estimators. ***, **, * indicate significance at 1%, 5% and 10% respectively.

Table 6. Robustness tests using Quantile regressions

	Before expiration				After expiration			
	Rm^2 D_{exp}	***p-value***	**Rm^2 (1-D_{exp})**	***p-value***	**Rm^2 D_{exp}**	***p-value***	**Rm^2 (1-D_{exp})**	***p-value***
D_0	-0.013186	*0.91*	0.106122***	*0.00*				
D_1	-0.142918	*0.29*	0.113435***	*0.00*	0.981784	*0.23*	0.107023***	*0.00*
D_2	-0.170789***	*0.00*	0.113514***	*0.00*	0.782161	*0.34*	0.107138***	*0.00*
D_3	-0.085632	*0.25*	0.112832***	*0.00*	-0.043864	*0.97*	0.107066***	*0.00*
D_4	-0.089831	*0.11*	0.112729***	*0.00*	-0.099513	*0.79*	0.106936***	*0.00*
D_5	-0.085813	*0.15*	0.111250***	*0.00*	0.367007	*0.78*	0.107200***	*0.00*
D_6	-0.055984	*0.29*	0.112948***	*0.00*	0.661392	*0.59*	0.107234***	*0.00*
D_7	-0.055442	*0.33*	0.111882***	*0.00*	-0.425801***	*0.00*	0.106638***	*0.00*
D_8	-0.090121**	*0.02*	0.112287***	*0.00*	-0.410641***	*0.00*	0.106639***	*0.00*
D_9	-0.128446*	*0.05*	0.113445***	*0.00*	-0.337711	*0.39*	0.106667***	*0.00*
D_{10}	-0.128106**	*0.02*	0.113516***	*0.00*	0.034026	*0.53*	0.114780***	*0.00*
D_{11}	-0.097982**	*0.01*	0.112689***	*0.00*	0.044743	*0.18*	0.113423***	*0.00*
D_{12}	-0.089636**	*0.02*	0.112217***	*0.00*	0.080440	*0.27*	0.113600***	*0.00*
D_{24}	-0.128187***	*0.00*	0.113447***	*0.00*	0.035516	*0.23*	0.107183***	*0.00*
D_{36}	-0.098464***	*0.00*	0.112197***	*0.00*	0.059866***	*0.00*	0.105874***	*0.00*
D_{48}	-0.087003***	*0.00*	0.110951***	*0.00*	0.060119***	*0.00*	0.113675***	*0.00*
D_{60}	-0.083854***	*0.00*	0.110769***	*0.00*	0.058194***	*0.00*	0.113647***	*0.00*
D_{72}	-0.054904	*0.84*	0.111672***	*0.00*	0.056161***	*0.00*	0.114722***	*0.00*
D_{84}	-0.045361	*0.85*	0.110657***	*0.00*	0.059461***	*0.00*	0.113765***	*0.00*
D_{96}	-0.078991***	*0.00*	0.109752***	*0.00*	0.060059***	*0.00*	0.113441***	*0.00*
D_{108}	-0.081603***	*0.00*	0.109956***	*0.00*	0.059868***	*0.00*	0.113845***	*0.00*
D_{120}	-0.035914	*0.88*	0.110315***	*0.00*	0.059316***	*0.00*	0.113899***	*0.00*
D_{132}	-0.040240	*0.86*	0.110850***	*0.00*	0.061740***	*0.00*	0.113383***	*0.00*
D_{144}	0.005853	*0.61*	0.111669***	*0.00*	0.063808***	*0.00*	0.111452***	*0.00*
D_{150}	0.004261	*0.71*	0.112111***	*0.00*	0.064497***	*0.00*	0.110977***	*0.00*

The table shows the estimates of Equation (3) including five lags of CSAD.

$$CSAD_t = \gamma_0 + \gamma_1 D_{\exp}|Rm_t| + \gamma_2(1-D_{\exp})|Rm_t| + \gamma_3 D_{\exp} Rm_t^2 + \gamma_4(1-D_{\exp})Rm_t^2 + \varepsilon_t$$

D_{exp} is the dummy variable, defined differently, that takes value 1 in specific times around expiration and 0 otherwise. Each raw contains the estimated parameters of the model for one dummy variable associated to D_{exp}. For example, the dummy variable D_1 takes a value of 1 one hour before (after) expiration and 0 otherwise; the dummy variable D_2 takes a value of 1 2 hours before (after) expiration and 0 otherwise and so on, until D_{150} that takes a value of 1 150 hours before (after) expiration and 0 otherwise. Results using Newey-West heteroscedasticity and autocorrelation consistent estimators. ***, **, * indicate significance at 1%, 5% and 10% respectively.

Table 7. Robustness tests using the CH(1995) model

	Extreme 1% lower market returns				Extreme 1% larger market returns			
	$D^L D_{exp}$	***p-value***	**$D^L(1\text{-}D_{exp})$**	***p-value***	**$D^U D_{exp}$**	***p-value***	**$D^L(1\text{-}D_{exp})$**	***p-value***
Aver. D_{0pre}-D_{150pre}	0.0004	*0.10*	0.0017	*0.00*	0.0004	*0.11*	0.0011	*0.00*
Aver. D_{1post}-$D_{150post}$	0.0007	*0.12*	0.0017	*0.00*	0.0005	*0.18*	0.0010	*0.00*
Aver. D_{4pre}-D_{8pre}	-0.0003	*0.00*	0.0016	*0.00*	0.0003	*0.21*	0.0010	*0.00*
Aver. D_{8post}-D_{11post}	0.0001	*0.59*	0.0016	*0.00*	-2.9E-05	*0.63*	0.0010	*0.00*

The table shows the estimates of the CH(1995) equations including five lags for the dispersion of returns.

$$CSSD_t = \alpha_0 + \beta_{11} D_{\exp} D_t^L + \beta_{12}(1 - D_{\exp}) D_t^L + \beta_{21} D_{\exp} D_t^U + \beta_{22}(1 - D_{\exp}) D_t^U + \varepsilon_t$$

D_{exp} is the dummy variable, defined differently, that takes value 1 in specific times around expiration and 0 otherwise. $D^L = 1$ if the market return at time t lies in the 1% extreme lower tail of the return distribution and 0 otherwise. $D^U = 1$ if the market return at time t lies in the 1% extreme upper tail of the return distribution and 0 otherwise. In the table: Aver. D_{4pre}-D_{8pre} is the variable representing the average of D_{exp} estimates (from D_{4pre} to D_{8pre}) and their average significance in parentheses (from D_{4pre} to D_{8pre}); Aver. D_{0pre}-D_{150pre} is the variable representing the average of D_{exp} estimates (from D_{0pre} to D_{150pre}) and their average significance in parentheses (from D_{0pre} to D_{150pre}); Aver. D_{8post}-D_{11post} is the variable representing the average of D_{exp} estimates (from D_{8post} to D_{11post}) and their average significance in parentheses (from D_{8post} to D_{11post}) and Aver. D_{1post}-$D_{150post}$ is the variable representing the average of D_{exp} estimates (from D_{1post} to $D_{150post}$) and their average significance in parentheses (from D_{1post} to $D_{150post}$).

Figure 1. Flow Chart of the analysis process.

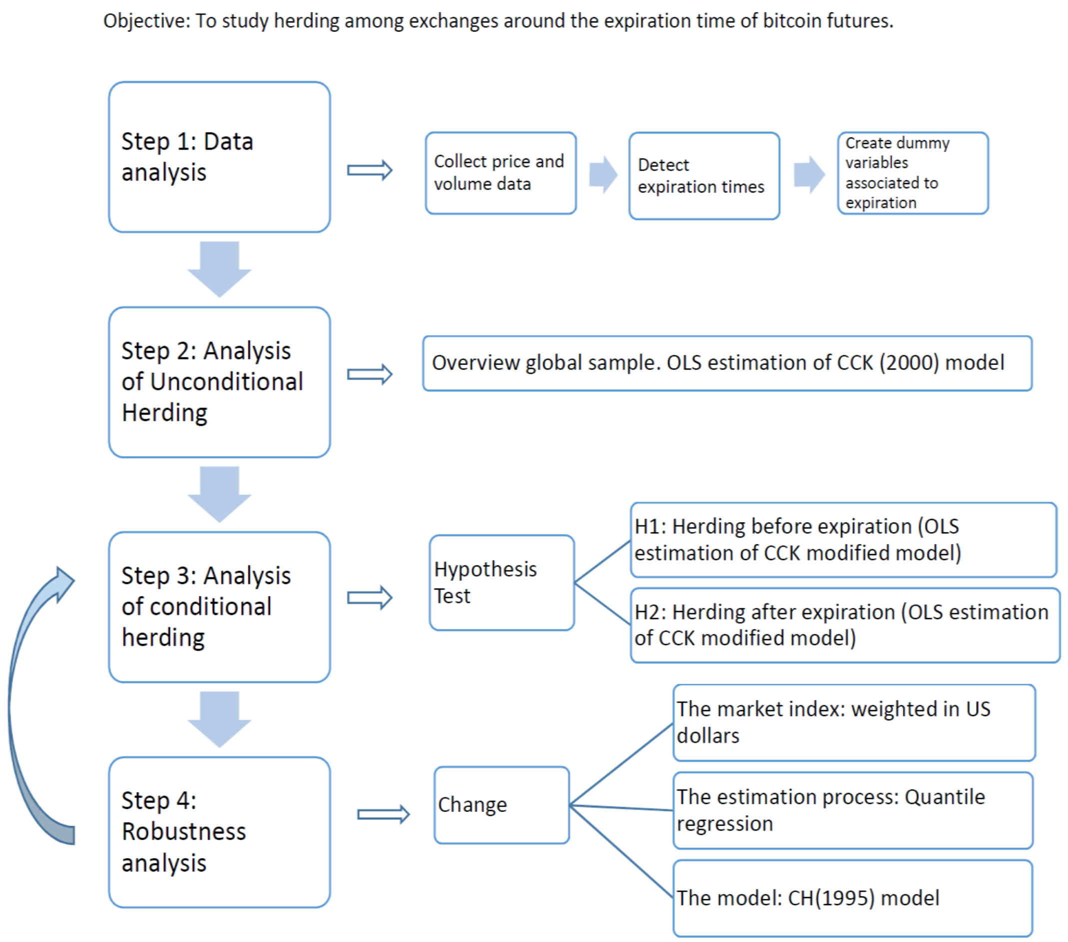
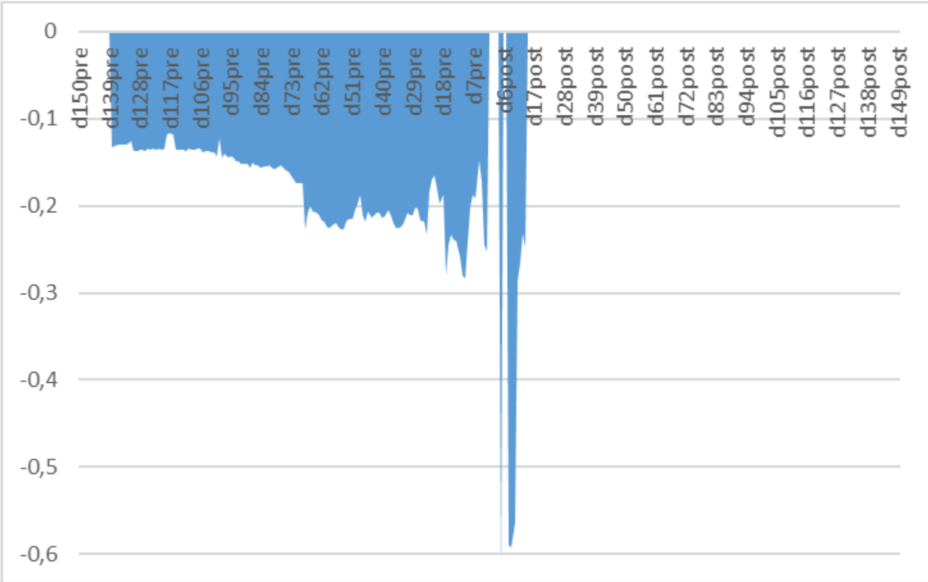


Figure 2. Estimates of significant herding coefficients around futures expiration.



PART 3: Some of the ingredients spicing up the bitcoin price: Covid, inflation and war

Some of the ingredients spicing up the bitcoin price: Covid, inflation and war.

Abstract:

This paper aims to study how some relevant news affects Bitcoin prices. For this analysis, we have considered the period from May 2018 to November 2023, during which the most relevant international information had to do with the Covid pandemic, inflation, the subsequent increase of interest rates, and the outbreak of the Ukraine-Russia conflict. After a preliminary examination, the final analysis is carried out in two stages using high-frequency data and news from Bloomberg. In the first stage, we use hourly prices for the complete period of study and highly significant news on Covid, inflation and war. In the second, we use second-by-second data from the CME BRTI for a selected number of crucial dates and highly significant news, other news on the topics under study, and other significant news unrelated to these topics.

Our findings are significant, suggesting that news on Covid and war can be anticipated for up to two hours by the market. This is due to the continuous release of information on these topics, which clearly impacts Bitcoin prices and may last for hours. In the case of inflation-related news, the release of information is typically previously scheduled and the impact is heavily concentrated around the publication time.

Our study reveals the importance of using the appropriate time frequency for this type of analysis to avoid misinterpretations of the results.

1. Introduction

Prices in financial markets are supposed to capture wholly and immediately all the information available in the market. From a theoretical perspective, the main issue of information-based models is how to include information in asset-pricing models. From a more practical point of view, the precise impact of some specific public information on prices in traditional financial markets has been widely analyzed for many years (Ederington and Lee (1993, 1995), Almeida et al. (1998), Blasco et al. (2005), Chen et al. (2016) and Maserumule & Alagidede (2017), among others). News can be considered an excellent example of public information that might be observed by any investor (informed or not).

For many years, Bitcoin has been said not to have any fundamental value and, therefore, it cannot be valued rationally (Cheah & Fry, 2015). Bitcoin is global; it is not directly related to the economic situation or the set of policies of a single company or country. Its decentralized nature and the absence of traditional valuation metrics generate prices largely driven by market demand, supply dynamics, and speculative sentiment. However, demand, supply and sentiment may be reinforced or weakened by information. People need information to socialize, to make decisions and formulate opinions.

Some studies have shown that different types of news, such as macroeconomic developments, pandemic news, media sentiment, and social signals from platforms such as X, formerly Twitter, can impact bitcoin prices (Gherghina & Simionescu, 2023; Chen et al., 2020; Zaman et al., 2022; Yelkenci et al., 2023; Pano & Kashef, 2020). For example, the impact of news announcements, such as the launch of Libra, has been shown to affect Bitcoin prices (Azouzi & Echchabi, 2019). Or, for example, the study of the impact of Chinese policies and regulations on Bitcoin highlights how economic policy uncertainty can significantly influence the volatility of the Bitcoin market (Wu & Wang, 2023). On the other hand, sentiment analysis of news and social media has been used to predict Bitcoin prices (Prajapati, 2020; Karalevicius et al., 2018). Furthermore, investor sentiment is found to play a crucial role in Bitcoin price dynamics, with evidence suggesting that positive returns can lead to even more bullish sentiments, causing Bitcoin prices to continue rising (Chevapatrakul & Mascia, 2019; Koutmos, 2022). Overall, the synthesis of these studies underscores the multifaceted nature of Bitcoin price formation, where news, sentiment, and external factors such as regulatory policies all contribute to the dynamic movements in Bitcoin prices.

Over the past five years, a confluence of significant global events has profoundly impacted the world economy. The Covid-19 pandemic, first and foremost, emerged as an unprecedented disruptor, causing widespread economic downturns as nations implemented strict lockdowns and travel restrictions to curb the virus's spread. This resulted in disruptions to supply chains, reduced consumer spending, and increased unemployment levels, whereas governments implemented massive stimulus packages to mitigate the economic fallout. Concurrently, the pandemic triggered an inflationary surge, posing challenges for central banks and policymakers. Against the backdrop of inflationary pressures, central banks grappled with the delicate balance of managing interest rates. As a result, interest rates remained relatively stable, affecting borrowing costs, investment decisions, and overall economic activity until the second quarter of 2022. Additionally, the geopolitical tensions between Russia and Ukraine escalated, further contributing to economic uncertainties. The conflict disrupted trade routes, impacted energy supplies, and heightened geopolitical tensions. Sanctions and geopolitical risks influenced investor confidence, affecting financial markets and economic stability.

In summary, the Covid-19 pandemic, inflation surge, interest rate dynamics, and geopolitical conflicts have collectively shaped the economic landscape over the past five years, underlining the interconnectedness and vulnerability of the global economic system.

In this context, the purpose of this paper is to test whether some specific global information (related to Covid-19, inflation, and war) affects Bitcoin prices and volume, as Bitcoin represents a type of global alternative political statement with underlying ideals of money free from government controls, inflation and taxation. The study is carried out with high trading frequency data, and the analysis extends from May 2018 to November 2023 so that the main topics of the research can be fully covered.

The work contributes to academic literature in two main lines. On the one hand, it delves into the impact that specific news events have on the return and trading volume of this asset, considering hourly data. On the other hand, it enriches the study of Bitcoin market price formation by examining the duration of the impact when using second-by-second data.

The paper is structured as follows: the next section describes the databases used in the two stages of the work (hourly data and second-by-second data), section 3 contains the empirical analysis, describing the methodology and the results obtained for both stages of the study, and finally section 4 highlights the main conclusions that can be drawn from the paper.

2. Data Base

In this empirical work, data from several sources of information have been integrated.

On the one hand, we needed news information on a specific topic. To determine the information about the news, we followed a series of steps. First, we initially constructed a news database from Proquest, which allows the selection of news based on specific terms. We have selected news including the keywords "inflation", "Covid", and "war" published in 100 relevant newspapers worldwide (American and Canadian, European, Asian, African, Australian and other Oceania countries). To facilitate the search process, the period of analysis was divided into five subperiods, for each of which we extracted the most significant 200 pieces of news related to each topic but not directly related to the two others[16]. For example, we extracted pieces of news related to inflation but not directly related with Covid or war. So, we ended up with a total of 3,000 news items, 1,000 per topic. The purpose of this selection was to avoid a high degree of contamination with any of the two other topics and to guarantee that each piece of news dealt mainly with the topic under study.

Second, with this information, we determined the specific days on which these pieces of news were published. We selected the 100 days with the most significant

[16] The Proquest database allows news to be ordered by relevance and excluding some main topics

information about Covid-19, 100 days with the most significant information about war, and 100 days with the most significant information about inflation. In other words, we identified the days with the highest accumulation of news on the topic in question. As a third step, we used the Bloomberg data service to extract all the specific news on these selected days related to Covid-19, war and inflation and their exact hour, minutes and seconds of publication (Proquest does not provide such information). Bloomberg terminals are heavily used in the financial marketplace, providing real-time market information from almost anywhere. In particular, we considered news sourced from Bloomberg First Word ("BFW"), as the time of publication is most likely the earliest one in existence, and BN (Bloomberg News) where it is classified as highly relevant. For the period under analysis, we have considered 523 pieces of news on Covid, 71 on the Russia-Ukraine war and 304 pieces of news on monetary policies and inflation.

The initial period under analysis precedes the onset of the Covid pandemic, the inflation issue and the Russian and Ukraine war. Subsequently, a second time frame emerges, coinciding with the surge in Covid-related information. Following this, there is a subsequent period intertwined with data on both Covid and inflation, notably highlighting uncertainties surrounding future interest rate hikes. The final period is marked by news concerning war, particularly the Russian invasion of Ukraine, as well as information about interest rate increases. It is important to note that this latter period can be subdivided into two subperiods. The first subperiod is characterized by heightened information on the outbreak of war, particularly in its initial months. In contrast, the second subperiod sees a reduction in war-related news but an increase in information regarding interest rate hikes and the implementation of restrictive monetary policies to combat inflation. Thus, news on Covid is heavily concentrated in March 2020 and from February to December 2021; news on war is highly concentrated between February and June 2022, and news on inflation is highly concentrated between December 2021 and June 2022.

On the other hand, we needed information on Bitcoin trading. We used 1-hour Bitcoin prices and volume, downloaded free from Bitstamp from

Cryptodatadownload[17]. We calculated absolute hourly returns for the period of study. We consider absolute returns as they give us the measure of the relevant price changes, either upwards or downwards, without the need to classify positive or negative interpretation of news and, therefore, without the need to identify good or bad news for the Bitcoin market, given the subjectivity this would imply. It is this hourly information that is used in the first stage of the empirical analysis.

Table 1 shows the main descriptive statistics of the price and volume of Bitcoin. We observe the high variability of the market variables. Both for return and volume, standard deviations are highly significant compared with the average values, supporting the popular message transmitted by some financial authorities that investment in Bitcoin is extremely volatile.

The second stage of the empirical analysis uses high-frequency information from the Bitcoin market; in particular, the BRTI data per second provided by the CME has been considered as additional information to illustrate the reaction of prices to specific pieces of news on some relevant dates. The CME CF Bitcoin Real Time Index (BRTI) is a benchmark index aggregating order data from Bitcoin-USD markets operated by major cryptocurrency exchanges. It is the pre-eminent price benchmark for real-time valuations and serves as a collateral valuation mechanism for trading on Crypto Facilities. At this stage, the type of news used is also expanded. This is described in more detail in the empirical analysis section.

As the primary purpose of the study is to test the price reactions to the arrival of new information, it is essential to note that all databases involved in each analysis have been homogenized, if needed, to the same time zone, even considering daylight saving time adjustments[18].

[17] https://www.cryptodatadownload.com/data/bitstamp/

[18] For example, BRTI is provided in Central Time (CT), and can vary between UTC-6 (Coordinated Universal Time-6) and UTC-5 depending on whether it is in standard time (winter) or daylight saving time (summer). Bitstamp provides information using Unix timestamp, the number of seconds (leap seconds are not applied) that have elapsed since January 1, 1970 (midnight UTC/GMT, defined as 00:00:00 UTC on January 1, 1970). Unlike Unix timestamps, UTC considers leap seconds. In turn, Bloomberg news reflects the current time zone of the computer receiving the information. Therefore, it is usually referenced to the corresponding local time.

3. Empirical Analysis

3.1. First stage: A look at Bitcoin prices in the middle distance. The reaction pattern in Bitcoin to information, using hourly prices.

The first stage of the analysis is to observe the reaction pattern of hourly Bitcoin prices to the external information (news about Covid, inflation and war). Specifically, we focus our study on absolute returns. The empirical model for returns has the following form:

$$ChangAbRent_t = \beta_0 + \beta_{1i}\sum_{i=1}^{k_1} ChangAbRent_{t-i} + \beta_{21}Ncovid_t + \beta_{22i}\sum_{i=1}^{k_2} Ncovid_{t-i} + \beta_{23i}\sum_{i=1}^{k_3} Ncovid_{t+i} + \beta_{31}Ninflation_t + \beta_{32i}\sum_{i=1}^{k_4} Ninflation_{t-i} + \beta_{33i}\sum_{i=1}^{k_5} Ninflation_{t+i} + \beta_{41}Nwar_t + \beta_{42i}\sum_{i=1}^{k_6} Nwar_{t-i} + \beta_{43i}\sum_{i=1}^{k_7} Nwar_{t+i} + u_t$$

$$(u_t/\emptyset_t) \approx N(0, h_t) \qquad h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 h_{t-1} \qquad (1)$$

The dependent variable *ChangAbRent$_t$* represents the change in the absolute value of the Bitcoin hourly return at hour t. Given the difficulty in classifying a news item as positive or negative, our work examines the impact of the publication of the news item on absolute returns. Studying the impact on returns directly would mean having to classify a news item as positive or negative. This classification involves an important degree of subjectivity, which can affect the conclusions drawn. It is also necessary to recognise the difficulty of such a classification at a given moment, when it is impossible to isolate a news item from its expectations or from other news items that may have been published earlier. This is why we have chosen to analyse the impact on absolute returns as a measure of the movements made by investors, both up and down.

However, although we are initially interested in analysing the absolute returns around the news, we include the absolute returns *in changes* given the significant first-order autocorrelation. This consideration helps to correct the possible positive feedback trading (or trend-chasing) described by De Long et al. (1990) and detected by Wang et al (2022) in the Bitcoin market.

Equation (1) includes three variables related to the time of a news item's release. Specifically, Ncovid, Ninflation and Nwar are dummy variables which take a value of 1 on the hours of the publication date of each piece of news (about Covid, inflation or war, respectively) and 0 otherwise. Moreover, both leads and lags have been included for the news dummy variables to check how long the reaction to a piece of news lasts and how long, although not published, it can be anticipated by the market. The number of leads and lags maximizes the log-likelihood function.

We use conditional volatility models, so Øt is the information set available on day t. Specifically, the GARCH(1,1) model has been considered to describe the variance behaviour adequately.

Since the dependent variable is the change in absolute return, a significant positive (negative) coefficient means that the news release is associated with an increase (decrease) in absolute return compared to the previous hour. The interpretation is related to the magnitude of the return and is a measure of investor uncertainty, similar to volatility. That is, if the magnitude of the return increases (both in the case of price increases and decreases), significant positive coefficients are found, and if the magnitude decreases, negative and significant coefficients are obtained. Finally, if the coefficient associated with the news is zero or not significant, this indicates that there is no variation in absolute return, i.e. the return is maintained with respect to the previous hour. This fact is compatible with an increase or decrease in prices similar to previous ones.

The estimation results are shown in Table 2. For clarity, only the coefficients associated with news dummy variables are included. Although not reported, the intercept and lags of the dependent variable, as well as the estimates for the GARCH(1,1) equation, are significant at the 1% significance level.

Generally, we can say that the results indicate that all the information about Covid, inflation or war is to a certain extent anticipated by the Bitcoin market before publication. Despite this common result, each type of news item leads to different behaviour. The table shows the results of the coefficients associated with the news both at the time of publication (event hour) and in the two hours before and two hours later[19].

The results are different for each type of news. In the case of Covid-related news, information is anticipated up to two hours before publication, and given that the dependent variable represents changes of absolute return, the interpretation of the results indicates that significant price changes (either upwards and downwards) are further accentuated until the publication time, and then the effect disappears after publication. War-related news is also anticipated two hours before publication, but the effect remains in the hour of publication. Finally, inflation-related news impacts Bitcoin prices immediately around the time of publication.

It should be taken into account that the three types of news are different. Covid-19 is a global health crisis that directly affects individuals' well-being and public health infrastructure, prompting widespread concern and urgency. Similarly, the Russian invasion has disrupted energy markets, leading to soaring prices globally, and the information focuses on military developments, diplomatic efforts, and humanitarian consequences. This piece of news addresses the personal impact on individuals. In contrast, news about inflation tends to focus on economic indicators and policies, influencing financial markets, business operations, and consumers' purchasing power. Central banks periodically monitor inflation and adjust interest rates to stabilize economies. Such periodicity probably makes the impact more closely visible around the publication time.

To complement the information provided by absolute returns, we now examine the possible impact on trading volume. Trading volume represents the consensus or divergence among investors and therefore its study can help to complete the picture. To investigate the effect of the publication of a piece of news on trading volume, we estimate the following model:

[19] We extended the analysis to 3, 4 and 5 hours before and after. The results are not significant in these cases.

$$ChangVol_t = \delta_0 + \delta_{1i} \sum_{i=1}^{l_1} ChangVol_{t-i} + \delta_{21} Ncovid_t + \delta_{22i} \sum_{i=1}^{l_2} Ncovid_{t-i} + \delta_{23i} \sum_{i=1}^{l_3} Ncovid_{t+i} + \delta_{31} Ninflation_t + \delta_{32i} \sum_{i=1}^{l_4} Ninflation_{t-i} + \delta_{33i} \sum_{i=1}^{l_5} Ninflation_{t+i} + \delta_{41} Nwar_t + \delta\beta_{42i} \sum_{i=1}^{l_6} Nwar_{t-i} + \delta_{43i} \sum_{i=1}^{l_7} Nwar_{t+i} + \omega_t$$

$$(\omega_t/\emptyset_t) \approx N(0, z_t) \qquad z_t = \alpha_0 + \alpha_1 \omega_{t-1}^2 + \alpha_2 z_{t-1} \tag{2}$$

Equation 2 shows the same structure as equation 1, although now the dependent variable *ChangVol*$_t$ is the change in trading volume (measured as number of bitcoins) traded at hour t. The trading volume is also calculated in changes to avoid autocorrelation problems. The rest of the variables are similar to the ones in equation 1.

Table 3 summarises the information on the coefficients of the dummy variables associated with the news. Consistent with the results for absolute returns, we observe a significant increase in trading volume two hours before the formal arrival of the news, confirming the market's anticipation in prices and correcting the impact thereafter. Up to the time of publication, inflation news has a significant impact on trading volume.

These results are consistent with those of Feng et al. (2017), who analysed the relevance of information related to Bitcoin market events (such as prohibitions, restrictions, recommendations, and hacking activities) and suggested that informed traders in the Bitcoin market profit significantly by building positions two days before large positive events and one day before large negative events.

Financial markets often exhibit reactions before the publication of news, indicating a level of anticipation and efficiency in processing information. Studies have shown that market reactions are primarily driven by business events and expectations among market participants rather than being solely influenced by follow-up reporting by financial news media (Strauß & Smith, 2019). This suggests that investors are proactive in incorporating available information into their trading decisions.

Moreover, research has indicated that market responses can occur before, on, and after the publication dates of annual financial reports (Julyana et al., 2022). This implies that market participants may have access to or interpret information prior to its official release, leading to anticipatory behaviors in the financial markets.

Then the question is: Are bitcoin traders informed traders? Natashekara and Sampath (2024) document the presence of informed trading in the cryptocurrency market, specifically through medium and small trades.

From another perspective, studies in behavioral economics have shown that individuals may exhibit anticipatory behaviors based on available cues and signals, leading to reactions before the formal dissemination of news. This suggests that human decision-making processes can be influenced by implicit information and external stimuli, potentially resulting in pre-emptive responses before official announcements. Moreover, research in psychology and communication studies has highlighted the role of cognitive biases and heuristics in shaping individual reactions to news and events (Ryan & Taffler, 2004). These cognitive mechanisms can prompt individuals to form expectations and responses ahead of concrete information release, indicating a degree of pre-emptive processing in human behavior. From the neurological perspective, studies have shown that the orbitofrontal cortex plays a role in encoding anticipated events, with subsets of neurons selectively responding to expected outcomes, even before formal confirmation (Schoenbaum & Setlow, 2001). This suggests that neural mechanisms are involved in processing anticipatory information and forming guesses regarding likely outcomes.

3.2. Second stage: A microscopic look at Bitcoin prices. The reaction pattern in Bitcoin prices to information, using the second-by-second CME BRTI

Having analysed the impact of news releases on hourly prices, in the second stage we want to go a little further and look at price formation in more detail. In the attempt to find more accurate patterns of price reaction to news, we find it convenient to use a more accurate data frequency and a broader news data set. For this purpose, we now consider second-by second prices. This analysis is computationally intensive and technically difficult to work with more than 176 million data per second that the 2018-2023 period encompasses. For this reason, we focus on a few specific days associated with large movements generated by the news items we have selected.

So, at this stage, we have selected a number of critical dates for each topic of news items. Moreover, we have considered all the relevant news provided by

Bloomberg, so that we now have included in our analysis not only BFW news (used in the first stage of this study) and most relevant BN news, but also any other BN (Bloomberg news) related or not to the corresponding key topic.

On the one hand, 11, 12 and 13 March 2020 have been chosen as representative of significant news on Covid. On March 11, 2020, the World Health Organization (WHO) officially declared Covid-19 a pandemic. This classification marked a critical turning point, triggering worldwide awareness and global urgent efforts to combat the virus. On March 12, additionally to death statistics, many central banks started to reveal financial support measures to combat the economic consequences of the pandemic. On March 13, 2020, President Donald Trump declared the Covid-19 outbreak a national emergency, further emphasizing the gravity of the situation. Hence, for 11, 12 and 13 March 2020, we now have BFW news and the most relevant BN news on Covid (13 pieces of news), other BN on Covid (31 pieces of news) and other BFW and BN non-Covid related news (47 pieces of news), a total of 91 news items and 258,964 absolute returns by second to analyse.

On the other hand, 15, 16 and 17 March 2022 have been selected as relevant days for news on monetary policy. On March 16, 2022, the Federal Open Market Committee (FOMC) raised the target range for the federal funds rate of 1/4 to 1/2 per cent and decided to begin reducing its Treasury securities and agency debt holdings. The Federal Reserve raised the interest rate paid on reserve balances to 0.4 per cent, effective on March 17, 2022. This move aimed to influence borrowing costs and manage liquidity in the financial system, essential measures to stabilize the economy and manage inflationary pressures. Similarly, the Bank of England raised its Bank Rate by 0.25 percentage points, bringing it to 0.75% on the same day, signalling its commitment to balancing inflation and economic growth. For 15, 16 and 17 March 2022, we now have BFW news and the most relevant BN news on inflation/interest rates (23 pieces of news), and other BFW and BN non-inflation related news (31 pieces of news). We have not found other not so relevant BN news on inflation for those dates, so we have a total of 54 news items and 259,200 absolute returns by second.

Finally, February 23, 24, and 25, 2022 have been chosen as pivotal days in the context of the Russian invasion of Ukraine. On February 24, Russia officially began its military invasion of Ukraine and triggered global alarm, with immediate reactions from governments, international organizations, and the public. For 23, 24 and 25 February 2022, we now have BFW news and the most relevant BN news on War (3 pieces of news), other BN on war (33 pieces of news) and other BFW and BN non-war related news (59 pieces of news), a total of 95 news items and 259,200 absolute returns by second.

Moreover, given that our results so far highlight the market's anticipation of news that will formally be released in the future, we consider it interesting to examine the actual impact that a particular news event has on Bitcoin prices after its formal publication. If news that has already been formally published has a real impact after publication, it may be that this impact helps to generate expectations about future information. It may also be the case that the aggregate sequence of many published news events and the aggregate sequence of their corresponding effects is what appears to be an early response to the publication of other news events later in time. It is worth noting at this point that significant volume reactions have been detected with confident anticipation before the publication of relevant news, so this reaction may also be a consequence of the existence of a chain of news events that are continuously sequenced over time rather than the specific publication of certain information. These explanations are also consistent with the fact that the frequency of the data may mask possible responses that cancel each other out or disappear over 60 minutes.

In order to assess the impact of specific news items, we focus on the study of absolute returns. We then perform a t-test to compare the mean absolute returns before and after the formal publication of the news, considering the exact second on which the piece of news is released[20]. The null hypothesis (H_0) assumes that there is no significant difference between absolute returns before and after the news release on some crucial dates. Otherwise, we consider that either before or after the news release, there is a significant impact on prices. To be consistent with the purpose of detecting the impact on prices, we only consider differences in mean lower than zero, as it is

[20] The degrees of freedom for the t-test depend on the sample sizes and whether the variances are assumed equal or unequal. We assume heterogeneity of variances (variances within each group are not similar, as we do not know whether news release may change volatility levels).

representative of higher price changes after publication but lower price changes before publication. This assumption implies that the information release is supposed to originate a significant change in prices that did not exist before, and therefore the absolute return after publication is higher than the absolute return before publication. At this stage, we are avoiding differences in mean higher than zero that could be identified with news anticipation, as our purpose is to detect when the information is processed, although such information processing can also contribute to the generation of expectations.

In order to analyse the differences in absolute returns before and after the publication of a news item, we propose two different strategies. In the first, we set the interval to 30 minutes before publication and take different time intervals after publication (5, 10, 15, 30, 45, 60, 90, 120, 150, 180, 210 and 240 minutes). For robustness, in the second we take different time intervals before publication of the news item and fix 30 minutes after publication. The time of publication is measured in hours, minutes and seconds according to the Chicago time zone, as we have considered the time series of Bitcoin prices provided by the CME CF Bitcoin Real Time Index (BRTI). For the time intervals, every-second absolute return has been calculated using the CME Bitcoin Real Time Index (BRTI).

The analysis of mean differences in absolute returns allows us to detect whether significant price changes have occurred after the publication (with significant lower than zero differences in mean), comparing the mean price changes immediately before the news publication and the period immediately after publication. The results over the different time intervals allow us to quantify how long an effect will last and the sensitivity of the results to time intervals.

The results are included in Tables 4 to 6. The tables show the averaged differences in the mean of absolute returns between times before and after every news publication by Bloomberg. For an easy interpretation of the results, significant negative differences revealing significant price changes are signalled with a number of "*" indicating the significance level. This significance level is calculated as the average significance level for each group of news. In addition to the average value, the tables include the percentage of significant negative differences for each group of news.

The Covid news information is summarised in Table 4. Column (1) shows differences in the mean of absolute returns between absolute returns 30 minutes before and absolute returns for some time after. In relevant news, we find that Covid news clearly impacts in the first 30 minutes after publication and, in fact, the effect lasts until 2 hours later. We found that more than 60% of the highly relevant news originates an impact of up to two hours when we compare the period 30 minutes before publication and several time lengths after. These results are robust to the previous reference period, as shown in column (2) that shows differences in the mean between absolute returns for a period of time before and absolute returns 30 minutes later. Irrespective of the period considered before (from 5 minutes to 2 hours before), the difference in absolute returns 30 minutes later is significant. We then looked at the reaction patterns of other news items about Covid that were published on those days and were not classified as highly relevant (and therefore not studied in the first stage of the study). In the case of these non-relevant news items, there is no difference in absolute returns after publication. In fact, as expected, relevant Covid news impacts more than other Covid news, which supports the classification done by Bloomberg. Finally, we observe the possible impact of non-Covid relevant news on these days. The pattern for such news shows that these news items move absolute returns 10 and 15 minutes after publication, and an effect is even observed two hours later. However, the percentage of influential news items is relatively low compared to that observed in the Covid news items, as it never exceeds 50%.

These results indicate that information published on Covid has a clear quick impact on Bitcoin prices and that this impact may last for some hours, allowing Bitcoin investors to anticipate other future information. In sum, the anticipation effect detected with hourly data may be due to the previous impact of some already published news, which, in turn, helps to forecast the information to come.

These results suggest the relevance of choosing the appropriate time intervals for the analysis. Based on our analysis of hourly data related to Covid news, we initially concluded that news is anticipated. However, when we examined second-by-second data, we found that news has a rapid impact in the moment and can also help to anticipate future information. The sequence of previously published news articles aids in constructing inferences and expectations about what will happen in the future.

Table 5 shows similar information but now with the results about pieces of news on war. In this case, relevant news items take at least two hours to perceive the impact produced if we compare prices 30 minutes before publication and after publication. The percentage of significant news in this case is 67%. Furthermore, if we look at what happens just 5 minutes before and 30 minutes after, the effect is also significant. Contrary to what happened in the news on Covid, other news items related to the war also have a significant quick effect on prices, as reactions are detected shortly after publication. It is important to note that the number of "other relevant news on war" (not included in the first stage of the study) is high compared to the number of "relevant news on war". Hence, it seems reasonable to think that this other information causes the anticipation of relevant future information detected with hourly data. Regarding the impact of news not related to the war on these days, it is observed that they do have an impact, but after at least 30 minutes. This suggests that during these days, the reaction to war-related news is more important than other topics.

Finally, Table 6 displays the differences in absolute returns around the publication of a piece of news on inflation. In the case of inflation and information about interest rates, only relevant news has been considered (other news items related to inflation are not available). As can be seen, in relevant news about inflation, the reaction to the information published is almost immediate and does not last long, in line with the results obtained with hourly data. The reaction of prices concentrates around the publication time (at most 30 minutes), although the percentage of significant news is between 33 and 44%. Other non- inflation news that occurs on these days also has an impact in the following minutes, although we do not observe the immediacy of inflation-relevant news, and the percentage of influential news is even lower than for inflation.

4. Conclusions

The aim of this paper is to explore the dynamics of Bitcoin price reactions to news releases. Specifically, we focus on three key events that occurred during the 2018-2023 analysis period: Covid, the Ukrainian war and inflation. To accomplish our goal, we have divided the paper into two stages. The first stage involves examining the price pattern at an hourly intraday frequency, which we may call the 'middle distance view'. The second stage involves examining the price behavior in detail (second-by-second), which we may call the ‘short distance view'.

Initially, the results obtained when examining the impact of a relevant news item on these topics with hourly data indicate that news about Covid and the war is anticipated in the markets, leading to large price fluctuations, probably due to the uncertainty involved. However, once the news is released, the impact does not seem to be sustained. In the case of inflation news, the impact is concentrated around the time of publication.

However, the analysis carried out with second-by-second data makes us cautious about the conclusions drawn from the hourly analysis. It should be remembered that this analysis is carried out for specific days, with absolute returns and including relevant and non-relevant news on the topic, as well as other news that occurred on those specific days, and is therefore not directly comparable with the hourly analysis. Nevertheless, the results obtained with this detailed information allow us to nuance some of the results derived from the analysis of the hourly data. In particular, we have observed that relevant news about Covid or war takes up to two hours to be processed after publication, while scheduled news with a specific date, such as the publication of inflation, has less impact over time. Additionally, other news stories, whether relevant or not, may have varying degrees of impact and duration depending on the topic, so excluding them from the analysis may influence the results obtained.

Our research has confirmed that it is difficult to determine the specific impact of a news item when there is related information that may create expectations about future news. Additionally, when the reaction to one news item coincides with the publication of the next, it can be challenging to isolate its effects. Therefore, it is essential to be precise in the temporal frequency of the data to avoid masking the true effects of a sequence of news items due to the proximity of other news item publications. We also believe that it is important to make further progress in identifying the news that is truly relevant to investors, as it is this news that moves markets. This work shows that there is still a long way to go to properly understand the information mechanisms that affect markets.

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Table 1. Descriptive statistics with hourly data.

	Mean	Standard Deviation	Median	Max	Min
Close price	22088.59	16152.84	18930.24	68627.01	3139.76
Return	3.03E-05	0.007490	6.35E-05	0.205482	-0.180903
Absolute return	0.004335	0.006108	0.002500	0.205482	0.000000
Volume BTC	31229.19	351237.53	125.86	24666622.48	0.000000
Volume BTC Variation	-0.000256	0.820806	-0.031054	10.92	-8.01

This table shows main descriptive statistics of hourly data of Bitcoin used in the first stage of the study.

Table 2. News and changes in absolute returns.

	Ncovid		Ninflation		Nwar	
	β_2	p-value	β_3	p-value	β_4	p-value
2 hours before	0.000672	0.003***	-7.26E-05	0.675	0.002007	0.000***
1 hour before	0.000401	0.090*	0.000299	0.071*	0.001651	0.001***
Event hour	-9.27E-05	0.768	0.000512	0.001***	0.001318	0.014**
1 hour later	0.000111	0.717	0.000358	0.016**	0.001064	0.115
2 hours later	0.000393	0.166	-5.43E-05	0.766	-0.000316	0.558

This table shows the estimates of the news parameters: β_{21}, β_{22i}, β_{23i}, β_{31}, β_{32i}, β_{33i}, β_{41}, β_{42i}, β_{43i}, with i=-2, -1, +1, +2, in eq. 1. $\beta_{21,}$ β_{21} and β_{21} represent estimates at time t (no lags, no leads) in eq.1. *, **, *** indicate that coefficients are significant at 10, 5 and 1% respectively.

$$ChangAbRent_t = \beta_0 + \beta_{1i}\sum_{i=1}^{k_1} ChangAbRent_{t-i} + \beta_{21}Ncovid_t + \beta_{22i}\sum_{i=1}^{k_2} Ncovid_{t-i} + \beta_{23i}\sum_{i=1}^{k_3} Ncovid_{t+i} + \beta_{31}Ninflation_t + \beta_{32i}\sum_{i=1}^{k_4} Ninflation_{t-i} + \beta_{33i}\sum_{i=1}^{k_5} Ninflation_{t+i} + \beta_{41}Nwar_t + \beta_{42i}\sum_{i=1}^{k_6} Nwar_{t-i} + \beta_{43i}\sum_{i=1}^{k_7} Nwar_{t+i} + u_t$$

$$(u_t/\emptyset_t) \approx N(0, h_t) \qquad h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 h_{t-1} \tag{1}$$

Table 3. News and changes in trading volume.

	Ncovid		Ninflation		Nwar	
	δ_2	p-value	δ_3	p-value	δ_4	p-value
2 hours before	0.097060	0.028**	0.048773	0.090*	0.205092	0.038*
1 hour before	0.029056	0.493	0.080497	0.006***	0.100234	0.291
Event hour	0.011151	0.793	0.069054	0.030**	-0.055873	0.592
1 hour later	-0.053207	0.204	-0.014384	0.649	0.163612	0.119
2 hours later	-0.057317	0.187	-0.055612	0.078*	0.054399	0.614

Estimates of the News parameters: δ_{21}, δ_{22i}, δ_{23i}, δ_{31}, δ_{32i}, δ_{33i}, δ_{41}, δ_{42i}, δ_{43i}, with i=-2, -1, +1, +2, in eq. 2. $\delta_{21,}$ δ_{21} and δ_{21} represent estimates at time t (no lags, no leads) in eq.2. *, **, *** indicate that coefficients are significant at 10, 5 and 1% respectively.

$$ChangVol_t = \delta_0 + \delta_{1i}\sum_{i=1}^{l_1} ChangVol_{t-i} + \delta_{21}Ncovid_t + \delta_{22i}\sum_{i=1}^{l_2} Ncovid_{t-i} + \delta_{23i}\sum_{i=1}^{l_3} Ncovid_{t+i} + \delta_{31}Ninflation_t + \delta_{32i}\sum_{i=1}^{l_4} Ninflation_{t-i} + \delta_{33i}\sum_{i=1}^{l_5} Ninflation_{t+i} + \delta_{41}Nwar_t + \delta\beta_{42i}\sum_{i=1}^{l_6} Nwar_{t-i} + \delta_{43i}\sum_{i=1}^{l_7} Nwar_{t+i} + \omega_t$$

$$(\omega_t/\emptyset_t) \approx N(0, z_t) \qquad z_t = \alpha_0 + \alpha_1 \omega_{t-1}^2 + \alpha_2 z_{t-1} \tag{2}$$

Table 4. Difference for absolute returns around the publication of a piece of news on days with important information on Covid.

	Covid Relevant news				Other Covid news				Non Covid relevant news			
	(1)		(2)		(1)		(2)		(1)		(2)	
Time	Diff.	%	Diff.	%	Diff.	%	Diff.	%	Diff.	%	Diff.	%
5´	23.29	8%	-18.1*	46%	1.91	23%	-6.64	32%	-7.24	17%	14.6	21%
10´	14.06	15%	-7.46	31%	7.73	23%	2.00	39%	-2.88*	26%	20.0	26%
15´	11.23	23%	-5.17*	38%	5.92	23%	3.12	32%	-2.42*	32%	13.8	23%
30´	-6.21*	54%	-6.21*	54%	4.50	29%	4.50	29%	0.47	23%	0.47	23%
45´	-11.09**	62%	-4.46*	46%	6.70	42%	0.05	32%	1.30	26%	-3.00	26%
60´	-12.10**	69%	-2.96	38%	9.61	39%	0.16	39%	2.40	36%	-0.13*	21%
90´	-13.95**	62%	-5.26*	38%	1.15	45%	6.14	39%	2.59	36%	3.95	23%
120´	-15.44**	62%	-5.41	38%	1.46	45%	6.78	45%	-5.83*	45%	1.13	28%

Table 4 displays the difference in mean for absolute returns before and after the publication of a piece of news on 11, 12 and 13 March 2020, days selected for Covid news. Differences are multiplied by 10^6. Columns (1) show differences in the mean of absolute returns between absolute returns 30 minutes before publication and absolute returns for some time after publication and % of significant negative differences; columns (2) show differences in the mean between absolute returns for some time before publication and absolute returns 30 minutes after publication and % of significant negative differences. *, **, *** indicate that differences are significant at 10, 5 and 1% respectively.

Table 5. Difference for absolute returns around the publication of a piece of news on days with important information on war.

	War Relevant news				Other war news				Non war relevant news			
	(1)		(2)		(1)		(2)		(1)		(2)	
Time	Diff.	%	Diff.	%	Diff.	%	Diff.	%	Diff.	%	Diff.	%
5´	-1.64	0%	-4.03***	67%	-4.15	30%	-2.92	45%	4.39	17%	0.07	31%
10´	3.05	0%	0.26	67%	-4.25	30%	-2.85*	52%	4.33	19%	-0.10	44%
15´	-0.18	33%	1.18	67%	-3.91*	39%	-3.41*	55%	3.13	22%	-0.54*	44%
30´	1.18	33%	1.18	33%	-2.73*	52%	-2.73*	52%	1.63	34%	1.63	34%
45´	-0.84	33%	3.15	0%	-2.77**	61%	-2.04*	42%	-0.85**	49%	2.36	36%
60´	-6.58	67%	3.20	0%	-4.55**	61%	-1.28**	36%	-1.61*	49%	2.35	41%
90´	-5.71	67%	3.05	0%	-5.93*	61%	1.64	33%	-1.54*	51%	2.09	41%
120´	-8.45*	67%	4.59	33%	-6.42*	67%	4.53	30%	-1.78*	54%	1.61	39%

Table 5 shows the difference in mean for absolute returns before and after the publication of a piece of news on 23, 24, and 25 February of 2022, days selected for war news. Differences are multiplied by 10^6. Columns (1) show differences in the mean of absolute returns between absolute returns 30 minutes before publication and absolute returns for some time after publication and % of significant negative differences; columns (2) show differences in the mean between absolute returns for some time before publication and absolute returns 30 minutes after publication and % of significant negative differences. *, **, *** indicate that differences are significant at 10, 5 and 1% respectively.

Table 6. Difference for absolute returns around the publication of a piece of news on days with important information on inflation.

	Inflation Relevant news				Non inflation relevant news			
	(1)		(2)		(1)		(2)	
Time	Diff.	%	Diff.	%	Diff.	%	Diff.	%
5´	-4.45*	33%	19.90	40%	3.41	23%	7.14	36%
10´	-2.43*	36%	15.50	36%	-0.16*	28%	0.93	31%
15´	1.57	24%	11.70	28%	-1.16*	33%	1.16	38%
30´	5.71	32%	5.71	32%	-0.69*	40%	-0.69*	40%
45´	7.33	24%	1.11	24%	0.94	42%	-1.29	38%
60´	8.61	28%	-0.60	24%	2.90	35%	-0.56	26%
90´	8.00	28%	-2.55***	44%	4.75	40%	0.83	33%
120´	8.84	28%	-2.75*	44%	6.27	40%	-0.93*	38%

Table 6 sets out the difference in mean for absolute returns before and after publication of a piece of news on 15, 16 and 17 March 2022, days selected for inflation news. Differences are multiplied by 10^6. Columns (1) show differences in the mean of absolute returns between absolute returns 30 minutes before publication and absolute returns for some time after publication and % of significant negative differences; columns (2) show differences in the mean between absolute returns for some time before publication and absolute returns 30 minutes after publication and % of significant negative differences. *, **, *** indicate that differences are significant at 10, 5 and 1% respectively.

Resumen y conclusiones

1. Resumen de la Tesis

El objetivo general de la tesis es contribuir a entender las dinámicas del mercado de Bitcoin y cómo diferentes factores internos y externos influyen en su comportamiento.

En particular, se exploran diversos aspectos relacionados con la formación del precio y el comportamiento de las principales variables financieras asociadas a la negociación del Bitcoin. Se presentan tres capítulos con un propósito común: desentrañar algunos de los motivos subyacentes en la fluctuación de precio, volatilidad y volumen de esta moneda. En conjunto, estos capítulos muestran que tanto el tradicional análisis fundamental racional como las finanzas conductuales (behavioral finance) son cruciales para comprender la totalidad de las dinámicas del mercado. La tesis pretende ayudar a la toma de decisiones de inversores y reguladores en un mercado altamente especulativo y emergente como el de las criptomonedas, aportando un enfoque integrado que considera conjuntamente las expectativas racionales y la psicología de los inversores que participan.

A continuación, se resumen los aspectos más relevantes de cada uno de ellos.

1.1. Capítulo 1: ¿Hay efecto vencimiento en el mercado de Bitcoin?

1.1.1. Introducción

El efecto vencimiento se define como una anomalía observada en el mercado del subyacente detectada alrededor de la fecha de vencimiento del derivado correspondiente. Las explicaciones tradicionalmente propuestas para dicho efecto se basan en el comportamiento de los inversores, las características de los sistemas de liquidación o la variedad de activos subyacentes y contratos de derivados, entre otros. Las razones de que se produzca este efecto se encuentran principalmente en el hecho de que, en los mercados de derivados, especuladores, coberturistas y arbitrajistas operan juntos. Sus acciones pueden afectar al flujo de información debido a los movimientos entre los mercados de contado y de derivados, especialmente en la fecha de vencimiento. Si esto ocurre se aprovechará la fecha de vencimiento para negociar más intensamente y se observará un volumen anormal. Dado que el volumen de negociación está estrechamente relacionado con la volatilidad, los movimientos en el volumen pueden dar lugar a cambios notables en la volatilidad y en la rentabilidad.

La irrupción de las criptomonedas en la economía y el desarrollo de mercados regulados de futuros sobre Bitcoin ofrecen una oportunidad para seguir avanzando en la comprensión de este fenómeno. En diciembre de 2017, CME y CBOE empezaron a negociar los futuros sobre Bitcoin, con la particularidad de que el activo subyacente no se negociaba en un mercado formalmente regulado. La introducción de futuros de Bitcoin en mercados regulados ha aumentado la popularidad de Bitcoin y permite ampliar la gama de activos con los que negociar y cubrir el riesgo, incorporando nuevos participantes a un mercado hasta ahora dominado por los inversores minoristas. La existencia de estos derivados puede atraer la atención de los inversores institucionales, lo que aumentará la liquidez del mercado. Los operadores pueden aprovechar los movimientos del Bitcoin sin necesidad de operar al contado. Además, los futuros de Bitcoin regulados permiten a los operadores operar en jurisdicciones en las que se han prohibido los criptoactivos.

Esta situación proporciona un marco ideal para desarrollar el objetivo de este capítulo, que consiste en analizar si el volumen de negociación, la volatilidad y la rentabilidad del Bitcoin se comportan de manera diferente en la fecha de vencimiento de los futuros sobre Bitcoin en comparación con los momentos de no vencimiento.

¿Deberíamos esperar un efecto vencimiento en el mercado del Bitcoin? Los argumentos son variados. Por un lado, los mercados de futuros de Bitcoin tienen volúmenes de negociación relativamente reducidos a pesar del atractivo para los inversores institucionales. Si el volumen de negociación de futuros es bajo, no deberíamos esperar efectos sobre los precios del Bitcoin. Por otra parte, los mercados de contado de Bitcoin también son relativamente pequeños, ilíquidos y poco profundos (en comparación con los mercados tradicionales). En este escenario, cualquier estrategia llevada a cabo por arbitrajistas y especuladores puede tener un mayor impacto en los precios, así como ser más susceptible a la manipulación. Además, el mercado de contado de Bitcoin es un mercado fragmentado. Esto significa que las estrategias pueden llevarse a cabo en varias bolsas. Si se produjeran efectos de desfase o discrepancias temporales de precios entre bolsas, las operaciones de arbitraje serían más fáciles de llevar a cabo para los operadores que incurren en bajos costes de transacción. Por consiguiente, cabe esperar un importante efecto vencimiento si los arbitrajistas, especuladores o manipuladores de precios deciden intervenir en el mercado.

El sistema de liquidación también tiene una implicación en el efecto vencimiento. Mercados de futuros como el CME y CBOE siguen un sistema de liquidación en efectivo que, a priori, afectaría en menor medida a los precios de contado al no ser necesaria la entrega del activo subyacente. Aunque comparten este patrón común, el tipo de referencia para la liquidación en el CME se basa en los precios del Bitcoin negociados en varias bolsas, mientras que en el CBOE se toma un precio de liquidación basado en la subasta en una sola bolsa. La plataforma Bakkt supervisada por Intercontinental Exchange (ICE) sigue un sistema de liquidación por entrega física y no requiere datos de precios del mercado al contado. Esta variedad de contratos nos permite dilucidar si el sistema de liquidación es relevante para el efecto vencimiento.

También hay que tener en cuenta que algunas bolsas relevantes negocian futuros de Bitcoin, aunque no estén regulados por instituciones tradicionales. Estos contratos de futuros pueden tener especificaciones diferentes, pero algunas fechas de vencimiento pueden coincidir con las de los regulados. En estos casos, si se detectara algún efecto vencimiento, no sería posible determinar la magnitud del efecto atribuible a cada contrato. No obstante, esta coincidencia carece de importancia dado que la mayor parte de los futuros negociados en mercados no regulados son futuros perpetuos.

Por último, cabe recordar que la negociación de los inversores institucionales puede desempeñar un papel decisivo alrededor de las fechas de vencimiento, ya que son inversores más sofisticados que pueden aprovechar algunas de las dificultades a las que se enfrentan los inversores individuales para encontrar oportunidades de beneficios. A medida que aumenta la participación de los inversores institucionales, aumenta también la posibilidad de encontrar un efecto de vencimiento.

1.1.2. Datos y metodología

El estudio se realiza en las siete bolsas de negociación más populares de Bitcoin. Cinco de ellas son bolsas constituyentes que proporcionan datos de precios para calcular los índices de referencia: Bitstamp, Coinbase, Itbit, Kraken y Gemini. También incluimos en el análisis otros dos mercados relevantes de Bitcoin: Binance y Bitfinex. Todas son bolsas centralizadas, empresas privadas que ofrecen plataformas de negociación que requieren el registro y la identificación de sus clientes, proporcionan mayor volumen y liquidez que las bolsas descentralizadas y atraen a inversores profesionales e institucionales.

Utilizamos datos diarios e intradiarios proporcionados por CryptoDataDownload. Los datos intradía son registros por hora y contienen los precios de apertura, cierre, máximo y mínimo del periodo y el volumen de negociación en BTC. El periodo total abarca desde el inicio de los contratos de futuros en diciembre de 2017 hasta el 20 de noviembre de 2020. El número total de observaciones es de 25.305 para cada variable y bolsa.

Para las fechas de vencimiento mensuales de los futuros de Bitcoin, hemos considerado tres mercados alternativos regulados. Los mercados regulados atraen a inversores institucionales, que se supone que toman decisiones basadas en información y contribuyen a la eficiencia del mercado.

Aunque el CBOE fue el primer mercado en negociar futuros sobre Bitcoin el 10 de diciembre, los contratos ofrecidos por el CME el 17 de diciembre, una semana después, desencadenaron el desarrollo de la negociación de futuros. Ambos contratos se expresan en dólares estadounidenses y las posiciones se liquidan por diferencias, en efectivo. Sin embargo, tanto el tamaño del contrato como la referencia del precio de liquidación difieren entre sí. El multiplicador del contrato de futuros negociado en el CBOE es de 1 Bitcoin y el valor de liquidación final de un contrato de futuros que vence es el precio oficial de subasta del Bitcoin en dólares estadounidenses determinado a las 16:00, hora de Nueva York, en la fecha de liquidación final por la subasta del Gemini Exchange. La fecha de liquidación final tiene lugar dos días hábiles (normalmente un miércoles) antes del tercer viernes del mes de vencimiento. Por su parte, el multiplicador del contrato de futuros de Bitcoin negociado en CME es de 5 Bitcoins y el precio de liquidación final es igual al CME Bitcoin Reference Rate (BRR) a las 16:00, hora de Londres, del último viernes del mes del contrato. El BRR es el índice compuesto por las cotizaciones de Bitcoin de varias bolsas constituyentes. Estas bolsas son Bitstamp, Coinbase, ItBit y Kraken (desde diciembre de 2017) y Gemini (desde el 30 de agosto de 2019).

El 23 de septiembre de 2019, el ICE introdujo un nuevo futuro regulado sobre Bitcoin. Este contrato se negocia en Bakkt y se diferencia de los dos anteriores en que se liquida físicamente. El tamaño del contrato es de 1 Bitcoin cotizado en dólares estadounidenses y la fecha de vencimiento es el tercer viernes del mes. La negociación en el mes de vencimiento del contrato cesa a las 14:30 hora de Nueva York del día hábil anterior al día de entrega del mes de contrato.

Hemos considerado la hora Unix como referencia para unificar la información horaria de todos los mercados analizados, ya que es ampliamente utilizada en sistemas operativos y formatos de archivo porque técnicamente no cambia sea cual sea la ubicación en el globo. También se ha tenido en cuenta el horario de verano.

Basándonos en los estudios previos se estudia el efecto del vencimiento en tres variables representativas del comportamiento del mercado, en concreto el volumen negociado, la volatilidad y la rentabilidad de los precios.

Para llevar a cabo el análisis se han estimado regresiones de series temporales. Todos los modelos incluyen como variables independientes el número necesario de retardos de la variable dependiente para controlar la autocorrelación y las variables ficticias de los días de la semana de lunes a sábado para evitar que la presencia de posibles efectos de estacionalidad diaria, interfiera con la fecha de vencimiento. Los modelos también incorporan una variable ficticia para detectar el efecto durante el periodo alrededor del vencimiento. Esta variable se diseña de distintas formas alternativas para tratar de recoger los efectos en las horas antes y después del vencimiento. En concreto se crean 24 variables ficticias que identifican el efecto acumulativo secuencial de las 24 horas anteriores al vencimiento y otras 24 que se identifican con las horas posteriores a la hora de vencimiento. Estas 48 variables ficticias se van incluyendo de forma alternativa en el modelo. Además, se han considerado los vencimientos de CME, CBOE y Bakkt por separado, así como el efecto conjunto de todos ellos. Así, finalmente se han estimado 576 modelos, utilizando 48 variables ficticias horarias acumuladas alternativas, sobre 3 variables de análisis (volumen, volatilidad y rentabilidad), para 4 referencias diferentes de fechas de vencimiento en función del mercado de futuros estudiado (CME, CBOE y Bakkt por separado y el efecto conjunto).

Los modelos empleados difieren dependiendo de la variable dependiente que se estudia. En el caso del volumen negociado, en el modelo se añade a las variables independientes ya comentadas, una variable adicional que recoge la tendencia temporal y que capta el aumento del volumen de negociación a lo largo del tiempo. Se han realizado estimaciones MCO teniendo en cuenta la matriz de varianzas y covarianzas consistente con heteroscedasticidad de Newey-West.

En cuanto a la volatilidad en este trabajo, se utiliza una medida de la volatilidad histórica con el fin de observar el efecto sobre los propios datos de negociación. En concreto utilizamos el estimador de volatilidad incondicional de Garman y Klass, estimador basado en rangos, insesgado y altamente eficiente en relación con otras medidas de volatilidad. Al igual que en el caso del volumen de negociación, realizamos regresiones MCO considerando la matriz de varianzas y covarianzas consistente con heteroscedasticidad de Newey-West.

Finalmente, el análisis de la rentabilidad, sigue los estándares habituales en la literatura y utiliza los modelos de volatilidad condicional que se ha comprobado se adaptan adecuadamente a las series de precios de los activos financieros. En concreto, en este caso se emplea el modelo GARCH asimétrico para recoger el comportamiento de la volatilidad condicional. El resto de variables independientes son las que se han descrito previamente.

Los análisis anteriores implican diferentes supuestos, como el cálculo de las variables, la definición del modelo de estimación o la naturaleza de la información utilizada, que podrían afectar a la interpretación de los resultados. Por ello, examinamos la robustez de los resultados, en primer lugar, siguiendo una metodología diferente en el proceso de estimación. Hemos realizado estimaciones agrupadas utilizando mínimos cuadrados con efectos fijos y errores estándar robustos. En segundo lugar, reestimamos los modelos utilizando el estimador de volatilidad de

Parkinson, que utiliza simplemente la información de los precios máximo y mínimo del Bitcoin. Por último, se ha realizado un análisis exhaustivo utilizando datos diarios en vez de intradiarios, considerando los posibles efectos durante la semana anterior y posterior al vencimiento.

1.1.3. Resultados y conclusiones

Los resultados relativos al volumen negociado indican que en las horas previas al vencimiento del contrato de futuros sobre Bitcoin del CME, se observa un impacto significativo en la negociación en todas las bolsas, con incrementos más fuertes en las horas cercanas al vencimiento y una disminución notable después de 14 horas. Este patrón también se observa en el vencimiento de los futuros de Bitcoin del CBOE, aunque de manera menos intensa. En contraste, los resultados para los vencimientos del futuro de bitcoin de Bakkt no siguen un patrón uniforme, ya que se observan descensos en el volumen negociado antes y después del vencimiento. Además, cuando se analiza el efecto conjunto de todos los vencimientos, se observa un resultado similar a la combinación de los coeficientes significativos de los vencimientos de CME y CBOE.

Los efectos en volatilidad van en línea con lo observado para el volumen negociado, con incrementos antes del vencimiento y descensos después, tanto para los vencimientos del CME como para los del CBOE. Cabe destacar que en el CBOE el efecto no es visible en el momento final del vencimiento, quizá debido al sistema de liquidación por subasta. En las horas posteriores al vencimiento, las bolsas no reaccionan inmediatamente, ya que tardan en reducir significativamente su volatilidad. El efecto del vencimiento de los futuros de Bitcoin de Bakkt, una vez más, difiere. El factor más relevante es que la volatilidad en el mercado de contado disminuye significativamente en el momento del vencimiento, una hora antes y una hora después. Por último, la agregación de los vencimientos para los tres mercados de futuros ofrece resultados homogéneos entre las bolsas y similares a los del CME, siendo los efectos más notables generalmente cerca de la hora de vencimiento.

Estos resultados analizados junto con los del volumen de negociación muestran que los efectos no son uniformes. Los efectos de los vencimientos CME y CBOE son similares en volumen y volatilidad, aunque con diferente intensidad. Ambas variables aumentan antes del vencimiento y disminuyen sustancialmente después. En el caso de los vencimientos de Bakkt, cuando se produce un efecto antes del vencimiento, éste es negativo sobre el volumen de negociación y la volatilidad. Sin embargo, los efectos después del vencimiento siguen la misma dirección para los tres contratos de futuros. Es muy probable que las diferencias en el procedimiento de entrega sean la causa de las diferencias en los resultados. En los mercados tradicionales, la mayoría de los contratos de futuros entregados físicamente se compensan o se refinancian antes del último día de negociación, sobre todo si el proceso de entrega es complejo. Esta práctica en los mercados de futuros podría ser una explicación factible del sorprendente descenso de la actividad en los mercados al contado antes de la fecha de vencimiento en los contratos de futuros con entrega física, presumiblemente utilizados sobre todo por los coberturistas. Por el contrario, los especuladores y arbitrajistas son potencialmente más proclives a utilizar futuros con liquidación en efectivo.

En cuanto a los efectos en la rentabilidad, tomando las fechas de vencimiento de los futuros de Bitcoin del CME, observamos que los rendimientos son significativamente superiores a la media antes del vencimiento y esto se repite horas después de la hora de vencimiento, resultados que pueden atribuirse a las diferentes zonas horarias en las que operan las bolsas. Los efectos en relación con el vencimiento de los futuros de Bitcoin del CBOE son escasos y nulos en el caso del vencimiento de los futuros del Bakkt. Los resultados teniendo en cuenta los vencimientos de los tres mercados en conjunto muestran una vez más un patrón similar a los resultados para los futuros CME.

Dado que el volumen negociado recoge la actividad de todos los tipos de participantes en el mercado, la variación detectada en el volumen de negociación en torno al vencimiento no puede atribuirse directamente a un tipo de inversor específico. Nuestros resultados indican que se identifican efectos de volumen en las bolsas constituyentes y no constituyentes. Las estrategias de arbitraje habituales entre las bolsas de contado (o los efectos de seguimiento entre las bolsas) podrían contribuir a explicar la actividad de negociación en torno al vencimiento en todas las bolsas.

Por otro lado, el efecto sobre la rentabilidad se atribuye a la liquidación de posiciones cortas de arbitraje. Estrategias basadas en vender Bitcoins en corto y comprar futuros por debajo de su precio podrían provocar desequilibrios en las órdenes de compra al deshacer posiciones y ser una explicación factible de nuestros resultados. Sin embargo, este tipo de estrategia de arbitraje no es fácil de aplicar en el mercado de Bitcoin: las operaciones de arbitraje pueden verse inhibidas por las diferencias de precios que cambian constantemente entre las bolsas constituyentes, así como por las fricciones de negociación en los mercados de futuros del CME.

A la luz de nuestros resultados sugerimos que, aunque teóricamente la participación conjunta de especuladores y arbitrajistas podría producir el efecto vencimiento, empíricamente es difícil distinguir el protagonismo de cada uno de estos actores. Sin embargo, las dificultades para llevar a cabo operaciones de arbitraje permiten cuestionar la prevalencia de este tipo de participantes en el mercado y resaltar el papel de los especuladores en los momentos próximos al vencimiento.

Los análisis realizados para ofrecer robustez apoyan en general los descritos previamente. La única cuestión reseñable aparece en el análisis realizado con datos diarios, ya que estos datos no permiten detectar un efecto claro en los días cercanos al vencimiento. Este hallazgo pone de manifiesto la relevancia de los datos intradía.

El solapamiento de posibles efectos de otros futuros no regulados con las mismas fechas de vencimiento que los de algunos de los futuros regulados objeto de análisis, así como el vencimiento de otros productos sofisticados como opciones o futuros con vencimiento diario, también pueden influir en los resultados mostrados. Sin embargo, los futuros perpetuos representan el mayor porcentaje de la negociación de futuros no regulados, por lo que no pueden producir un efecto de vencimiento. Además, los futuros regulados atraen a inversores institucionales, cuyo sólido acceso a la información probablemente influya en la negociación entre inversores minoristas y contribuya a explicar los efectos de vencimiento.

Una explicación adicional que puede ofrecerse sobre las diferencias entre los vencimientos de los distintos mercados tiene que ver con el multiplicador asociado a las especificaciones de los contratos de futuros. En el caso de CME, el tamaño de cinco Bitcoins frente al de 1 Bitcoin de los contratos de CBOE o Bakkt puede amplificar el efecto. Los inversores institucionales tienden a ser inversores sofisticados en comparación con los inversores minoristas. Esto significa que los operadores institucionales pueden encontrar oportunidades de arbitraje y especulación con más frecuencia que los operadores minoristas. La participación institucional puede reforzar el efecto de vencimiento. Estas explicaciones también son coherentes con el hecho de que los vencimientos en el CME son dominantes.

Este estudio tiene implicaciones especialmente para los reguladores en la medida en que el Bitcoin se convierta en un medio de pago generalizado. Detectar y controlar posibles anomalías en la fijación de precios sería una cuestión necesaria, para lo cual se requerirían acciones consensuadas entre los distintos agentes implicados en los distintos mercados.

1.2. Capítulo 2: Herding entre mercados de Bitcoin en la semana bruja

1.2.1. Introducción

Las finanzas conductuales tratan de explicar cómo los inversores toman decisiones en un contexto de racionalidad limitada, haciendo compatible la hipótesis del mercado eficiente con algunas regularidades empíricas observadas en los mercados financieros. En este marco, el comportamiento gregario ha suscitado especial interés en las tres últimas décadas. En los mercados financieros, el efecto manada o efecto gregario, habitualmente conocido como herding, se produce cuando algunos inversores deciden dejar de lado sus creencias y opiniones e imitar las decisiones de otros inversores a los que consideran mejor informados. En un contexto de racionalidad limitada, cuando la información privada de los individuos se ve desbordada por la influencia de la información pública, muchos inversores pueden tender a seguir el consenso del mercado.

Entre la variedad de razones que explican el comportamiento herding en los mercados financieros, destacan los costes de reputación, el sector de actividad al que pertenece una empresa e incluso algunas variables asociadas a la calidad de un determinado entorno informativo. No obstante, la reacción de los inversores ante la llegada de información es un aspecto clave común en todos ellos. El comportamiento mimético se ha relacionado o bien con reacciones similares de los inversores ante un conjunto de información o bien con la falta de información de calidad. Esta última induce el contagio en las decisiones cuando los inversores adquieren información (ruidosa) observando las acciones de otros agentes. También se ha observado que momentos con fluctuaciones repentinas de los precios pueden provocar un comportamiento mimético. Desde otra perspectiva, el herding puede surgir si la evolución de la opinión tiende al consenso.

El herding se ha estudiado tradicionalmente en diversos mercados de todo el mundo, en fondos institucionales e incluso entre analistas financieros. En los últimos años, sin embargo, el auge de las criptomonedas ha abierto un nuevo campo de estudio en relación con este fenómeno de comportamiento, ya que las criptomonedas ofrecen un nuevo marco informativo que presumiblemente difiere del de los mercados financieros más tradicionales. Las secuencias de información entre diferentes criptodivisas pueden tener características peculiares en comparación con las acciones, los bonos u otras divisas, especialmente debido no sólo al espíritu y la tecnología subyacentes de este nuevo tipo de activo, sino también a otros indicadores del mercado al contado como la liquidez, la escalabilidad y la falta de reconocimiento oficial. Las criptodivisas por sus características tienen el papel de inversión alternativa y, por tanto, son fuente de diversificación, al tiempo que cuentan con cierta correlación entre mercados específicos en momentos concretos. Todas estas características pueden modificar la reacción esperada de los inversores.

La tecnología subyacente, blockchain, la información proporcionada por las redes sociales que suscitan un creciente interés por estos nuevos productos y la información generada dentro de las propias criptobolsas permiten a los inversores disponer de un conjunto aparentemente más completo de información que no está tan fácilmente disponible para otros productos financieros. Aunque algunas de sus características deberían contribuir a una mayor transparencia informativa, la falta de regulación internacional clara, así como la aparición de una sobrecarga de información, pueden socavar dicha transparencia.

Al igual que la apertura y el cierre de cualquier sesión bursátil, la fecha de vencimiento se ha identificado como un momento revelador de información. Se supone que los mercados de contado que tienen un mercado de derivados asociado son más completos, ya que permiten una gama más amplia de estrategias de arbitraje y cobertura, incluso de manipulación de precios. En la fecha de vencimiento, los inversores deben decidir sobre su posición en el mercado, ya sea cerrando y liquidando, reequilibrando o refinanciando, en función de su información y sus expectativas. De hecho, la llamada hora bruja (la última hora de negociación cuando vencen los contratos de opciones y futuros) suele caracterizarse por un gran volumen de negociación, ya que los operadores cierran o renuevan sus posiciones antes del vencimiento. A su vez, estas decisiones generan nueva información. Todos estos flujos de información adicionales que revelan las estrategias de los inversores sofisticados, sumados al conjunto de información habitual que también afecta en las fechas de no vencimiento, pueden fomentar notablemente el comportamiento mimético entre los inversores.

Los mercados de criptodivisas no están exentos de estos efectos en las fechas de vencimiento de los futuros. Desde diciembre de 2017, cuando el CBOE y el CME comenzaron a negociar futuros regulados de Bitcoin, los inversores han mostrado una participación activa en este mercado y, por lo tanto, sus estrategias pueden haber inducido efectos de rebaño en el mercado al contado de Bitcoin en torno a las fechas de vencimiento.

El objetivo de este trabajo es analizar la presencia de herding entre las bolsas de Bitcoin en un momento en el que el flujo informativo puede cambiar notablemente, en concreto alrededor de la fecha vencimiento de los futuros de Bitcoin. Siguiendo la propuesta frecuentemente utilizada de Chang, Cheng y Khorana (2000) (CCK), ampliamos su modelo para analizar el efecto gregario en la fecha de vencimiento de los contratos de futuros de Bitcoin negociados en el CME, que han demostrado ser los más influyentes en el análisis llevado a cabo en el capítulo anterior. Por tanto, estudiamos si existe un comportamiento gregario condicionado al acontecimiento del vencimiento CME.

1.2.2. Datos y metodología

Los contratos de futuros de Bitcoin negociados en mercados regulados comenzaron su andadura en diciembre de 2017. Con solo una semana de diferencia, el CBOE y el CME lanzaron sus respectivos contratos de futuros (el 10 y el 17 de diciembre, respectivamente). Poco después, en septiembre de 2019, el Intercontinental Exchange (ICE) introdujo un nuevo contrato de futuros de Bitcoin negociado en la plataforma Bakkt.

Para considerar el mayor número posible de observaciones, nos centramos en los contratos de futuros ofrecidos por el CME, que se han mantenido uniformes durante el periodo de análisis y registran el mayor volumen de negociación de los tres mercados regulados. El vencimiento de este contrato de futuros tiene lugar el último viernes de cada mes a las 16:00, hora de Londres, y el precio de liquidación se basa en el Índice de Referencia del Bitcoin (BRR) calculado por el CME. El BRR es un índice de referencia diario que agrega las cotizaciones de Bitcoin de las principales bolsas al contado para garantizar su credibilidad. Las bolsas constituyentes son Bitstamp, Coinbase, itBit y Kraken (desde diciembre de 2017), así como Gemini (desde el 30 de agosto de 2019). El multiplicador del contrato es de 5 Bitcoins, la cotización se expresa en dólares estadounidenses y céntimos por Bitcoin, y el método de liquidación es en efectivo.

Tomamos los precios horarios del Bitcoin de siete bolsas relevantes. En concreto, se eligen Bitstamp, Coinbase, itBit, Kraken y Gemini, que son las bolsas constituyentes del contrato del CME. También incluimos Binance y Bitfinex, ya que son referencias claras en términos de volumen de negociación. La distribución geográfica de las sedes y oficinas de registro de todas las bolsas analizadas, así como la distribución geográfica de sus plataformas y servicios electrónicos, permiten una cobertura mundial del comercio de Bitcoins, lo que da solidez a nuestros resultados. Nuestra base de datos abarca desde diciembre de 2017 hasta octubre de 2020. La fuente de datos es CryptoDataDownload, que ofrece precios de cierre cada hora y volúmenes de negociación en Bitcoin y dólares estadounidenses. Se toma Unix Timestamp para unificar la información horaria de todos los mercados analizados. El horario de verano también se tiene en cuenta al convertir la marca de tiempo Unix en hora local.

El análisis realizado se lleva a cabo en dos fases, la primera consiste en estudiar el comportamiento herding incondicional y la segunda en estudiar dicho comportamiento condicionado a la fecha de vencimiento de los futuros.

Para llevar a cabo el análisis incondicional, empleamos el modelo CCK. Este establece una relación no lineal entre la desviación absoluta de sección cruzada de los rendimientos de los activos (CSAD) y el rendimiento del mercado. En presencia de herding, un gran movimiento de los rendimientos del mercado conllevará una reducción no lineal de la medida CSAD. Por tanto, el herding se presenta cuando esta relación no lineal es significativa y negativa. En el trabajo, adaptamos esta propuesta considerando la desviación típica de sección cruzada de los precios de las siete bolsas analizadas y como valor de mercado se toma la ponderación de sus rentabilidades, basándonos en el volumen negociado de Bitcoin. El modelo también incluye cinco retardos de la variable dependiente para corregir la autocorrelación. La estimación se realiza con mínimos cuadrados ordinarios (MCO) utilizando la matriz de varianzas y covarianza de Newey-West consistente con heteroscedasticidad y autocorrelación.

La segunda fase consiste en ampliar el modelo anterior siguiendo la propuesta de Zhou y Anderson (2013). En esta extensión, el modelo está condicionado por el evento específico del vencimiento de los futuros de Bitcoin. Para ello, incluimos en el modelo una variable ficticia, que identifica un intervalo de tiempo concreto asociado al vencimiento, y que se incluye moderando todas las variables independientes del modelo base. Esta variable ficticia toma diversas formas que se van alternando en el modelo. En concreto, se parte de una variable que toma valor uno en la hora del vencimiento y cero en el resto de horas y a continuación se crean otras 24 variables ficticias que van recogiendo las sucesivas acumulaciones de horas antes del vencimiento. Lo mismo se repite para las 24 horas posteriores, de forma que contamos finalmente con 48 variables ficticias asociadas a las horas alrededor del vencimiento.

En otros estudios de mercados tradicionales se han detectado flujos informativos muy intensos en torno a la semana de vencimiento que provocan cambios significativos en algunas medidas de negociación. De hecho, el concepto anteriormente mencionado de “hora bruja” puede ampliarse a la denominada “cuádruple hora bruja” si coinciden los vencimientos de varios derivados. La “cuádruple hora bruja” suele estar relacionada con volúmenes y rendimientos anormales en los días próximos al vencimiento. En el mercado de Bitcoin, existe una gama de contratos de futuros diferentes, tanto regulados como no regulados, y muchos de ellos tienen una fecha de vencimiento próxima al vencimiento del contrato de futuros CME, que identificamos como el más relevante. La posibilidad de una “hora bruja múltiple” podría hacer que los cambios en el comportamiento de los inversores durasen más de un día.

Teniendo en cuenta estas circunstancias, también creamos variables ficticias para hasta 150 horas antes y después de la hora de vencimiento. Estas variables adicionales pretenden detectar el posible efecto imitador aproximadamente 5 días antes y después del vencimiento. Es decir, exploramos la posible existencia de “semanas brujas”. Por tanto, finalmente estimamos 300 regresiones siguiendo el mismo procedimiento descrito previamente.

Para garantizar la solidez de los resultados, los modelos se vuelven a estimar utilizando una rentabilidad de mercado calculada como el índice ponderado por el volumen de Bitcoins negociados en USD. Además, como estimación alternativa, utilizamos el procedimiento de regresión cuantil que permite estimar el modelo en diferentes cuartiles de una distribución, en concreto utilizamos el cuartil 50 de la distribución de la variable dependiente. Finalmente se emplea el modelo seminal de Christie y Huang (1995) (CH) para medir el comportamiento herding basado en observar el comportamiento de los precios en los valores positivos y negativos extremos.

1.2.3. Resultados y conclusiones

Los primeros resultados se refieren a la estimación del modelo incondicional donde no encontramos evidencia de herding, sino al contrario. A la luz de estos primeros resultados de anti-herding, pasamos a estudiar el efecto condicionado al evento específico del vencimiento de futuros.

Los resultados cuando se estudia lo que ocurre la semana previa al vencimiento indican que, tanto en el momento del vencimiento como una hora antes, no existe un efecto herding significativo. Sin embargo, este efecto sí se aprecia a partir de dos horas antes del vencimiento, y se extiende no sólo hasta 24 horas (un día) antes del vencimiento, sino también hasta 137 horas antes del vencimiento, momento a partir del cual el parámetro herding deja de ser significativo. Cuando se estudia lo que ocurre la semana siguiente al vencimiento, los resultados muestran que no hay herding en las horas más próximas al vencimiento. Sin embargo, este comportamiento sí que aparece desde 7 horas hasta 12 horas después del vencimiento, probablemente porque los inversores reabren activamente nuevas posiciones y generan un nuevo exceso de información, aunque más breve, que fomenta el comportamiento mimético. A partir de ese momento, en línea con los resultados para los días sin vencimiento y los resultados incondicionales, el herding desaparece. La lectura conjunta de los resultados indica que el efecto gregario empieza a disminuir 13 horas después del vencimiento y posteriormente se convierte en un comportamiento anti-herding.

En cuanto al concepto de semana bruja respecto al volumen, el volumen de negociación de las bolsas que pertenecen a nuestra muestra crece aproximadamente un 2% al principio de la semana de vencimiento, alcanzando un aumento de aproximadamente el 5,5% en las 24 horas anteriores al vencimiento. Estos aumentos se corrigen, a un ritmo similar, después del vencimiento. Los incrementos de volumen previos al vencimiento son coherentes con el exceso de información en esos momentos (y, por tanto, con la dificultad de procesarla) y con el incentivo de las prácticas de herding que desaparecen tras el vencimiento.

Los análisis de robustez utilizando otro índice de mercado, y la estimación con la regresión cuantil, permiten confirmar que los resultados no dependen del índice ni del método de estimación considerado. Sin embargo, la utilización del modelo CH para estimar el herding no ofrece resultados convincentes. Esta divergencia se debe a que aproximadamente el 98,7% del 1% de los rendimientos positivos extremos y del 1% de los rendimientos negativos extremos de nuestro periodo de análisis corresponden a periodos sin vencimiento, por lo que este método no parece ser el más adecuado para detectar herding alrededor de la fecha de vencimiento. No obstante, el modelo CH confirma el comportamiento contrario al herding en los días sin vencimiento y la notable relación lineal entre las medidas de dispersión y los rendimientos extremos del mercado.

En conjunto, los resultados nos llevan a concluir que existe una reacción diferencial de los inversores alrededor del vencimiento de los futuros de Bitcoin en comparación con los momentos de no vencimiento. Cuando los contratos de futuros de Bitcoin llegan a su vencimiento, los inversores que operan en distintas bolsas se imitan unos a otros. Este comportamiento gregario también se produce unas horas después del vencimiento, probablemente debido al reajuste de estrategias que tiene lugar tras el vencimiento y a la reapertura de contratos que vencerán en una fecha posterior. Fuera de las horas próximas al vencimiento, los inversores no se imitan entre sí de forma significativa. De hecho, en general se observa un claro comportamiento antiherding.

Los cambios informativos alrededor del vencimiento inducen cambios en el comportamiento de los inversores, ya que su reacción cambia de tomar decisiones por su cuenta a imitarse unos a otros, probablemente debido a la sobrecarga de información que dificulta la toma de decisiones de los inversores. El herding puede parecer una alternativa adecuada para tomar decisiones aparentemente informadas cuando los inversores no pueden gestionar el exceso de información. Aunque aparece cierto herding tras el vencimiento, no dura mucho y supuestamente da lugar a la reacción anti-herding que se mantiene básicamente hasta la siguiente semana de vencimiento.

Durante la semana de vencimiento, muchos inversores imitan las decisiones de otros, propagando la imitación a través de diferentes mercados y plataformas, amplificando los posibles precios erróneos del Bitcoin y aumentando la volatilidad. Esto dificulta la predicción adecuada de los precios y eleva el riesgo asumido por los inversores. Además, los diferenciales de precios se estrechan cerca del vencimiento, limitando las oportunidades de beneficios para los arbitrajistas y coberturistas. Los arbitrajistas deben revisar sus estrategias, especialmente en el arbitraje triangular y en la cobertura en los mercados al contado y de futuros.

Los responsables políticos y reguladores del mercado deben tener en cuenta que la semana de vencimiento es atípica, con bolsas que siguen el consenso del mercado, lo cual podría ser preocupante en caso de grandes fluctuaciones. La toma de decisiones es crucial en los mercados financieros, y el herding es una consecuencia de estas decisiones. En el futuro, se necesita investigación interdisciplinar para entender mejor el comportamiento de los inversores en los mercados financieros.

Estos resultados ponen en evidencia la necesidad de seguir trabajando en comprender la conducta y psicología de los inversores. Factores como el miedo a perderse algo (FOMO), por sus siglas en inglés), el sesgo de confirmación y el exceso de confianza pueden provocar decisiones que motiven comportamientos como el herding. El fuerte crecimiento del comercio de Bitcoin es, en sí mismo, resultado de factores psicológicos que hacen que este análisis sea aún más interesante.

1.3. Capítulo 3: Algunos de los ingredientes que condimentan el precio del bitcoin: Covid, inflación y guerra.

1.3.1. Introducción

Los precios de los mercados financieros deben reflejar de manera completa e inmediata toda la información disponible. El principal desafío de los modelos teóricos de valoración es cómo integrar la información en tales modelos. Desde un punto de vista más práctico, el impacto de la información pública sobre los precios en los mercados financieros tradicionales ha sido ampliamente estudiado durante años. En concreto, la información producida vía noticias es el ejemplo de información pública que puede ser observada por cualquier inversor, ya sea informado o no y que se ha analizado con más intensidad.

Desde otra perspectiva, los estudios en economía conductual han demostrado que los individuos pueden mostrar comportamientos anticipatorios basados en indicios y señales disponibles, que conducen a reacciones antes de la difusión formal de las noticias. Esto sugiere que los procesos humanos de toma de decisiones pueden verse influidos por información implícita y estímulos externos, lo que puede dar lugar a respuestas preventivas antes de los anuncios oficiales. Además, la investigación en psicología y comunicación ha puesto de relieve el papel de los sesgos cognitivos y los heurísticos en la formación de las reacciones individuales a las noticias y los precios. Estos mecanismos cognitivos pueden inducir a los individuos a crear expectativas y respuestas antes de que se publique la información concreta, lo que indica cierto grado de procesamiento preventivo en el comportamiento humano.

Bitcoin es un activo global; no está directamente relacionado con la situación económica o el conjunto de políticas de una sola empresa o país. Su naturaleza descentralizada y la ausencia de métricas de valoración tradicionales generan precios impulsados en gran medida por la demanda del mercado, la dinámica de la oferta y el sentimiento especulativo. Sin embargo, la demanda, la oferta y el sentimiento pueden verse reforzados o debilitados por la información.

En este sentido, algunos estudios han demostrado que distintos tipos de noticias, como la evolución macroeconómica, las noticias sobre pandemias o regulaciones, pueden influir en los precios del Bitcoin. Pero, además, el sentimiento de los medios de comunicación y las señales sociales de plataformas como X, contribuyen a los movimientos dinámicos de los precios de Bitcoin.

En los últimos cinco años, una confluencia de importantes acontecimientos globales ha afectado profundamente a la economía mundial. La pandemia del Covid-19, en primer lugar, se erigió en un factor de perturbación sin precedentes, provocando crisis económicas generalizadas a medida que los países aplicaban estrictos cierres patronales y restricciones a los viajes para frenar la propagación del virus. Esto provocó interrupciones en las cadenas de suministro, redujo el gasto de los consumidores y aumentó los niveles de desempleo, mientras que los gobiernos aplicaron paquetes de estímulo masivo para mitigar las consecuencias económicas. Al mismo tiempo, la pandemia desencadenó un repunte inflacionista que planteó retos a los bancos centrales y a los responsables políticos. Con las presiones inflacionistas como telón de fondo, los bancos centrales se enfrentaron al delicado equilibrio de gestionar los tipos de interés. Como resultado, los tipos de interés se mantuvieron relativamente estables, afectando a los costes de endeudamiento, las decisiones de inversión y la actividad económica general hasta el segundo trimestre de 2022. Además, las tensiones geopolíticas entre Rusia y Ucrania se intensificaron, contribuyendo aún más a la incertidumbre económica. El conflicto interrumpió las rutas comerciales, afectó al suministro de energía y aumentó las tensiones geopolíticas. Las sanciones y los riesgos geopolíticos influyeron en la confianza de los inversores, afectando a los mercados financieros y a la estabilidad económica.

En resumen, la pandemia del Covid-19, el repunte de la inflación, la dinámica de los tipos de interés y los conflictos geopolíticos han configurado colectivamente el panorama económico de los últimos cinco años, subrayando la interconexión y la vulnerabilidad del sistema económico mundial.

En este contexto, el objetivo de este capítulo es analizar si cierta información específica relacionada con el Covid-19, la inflación y la guerra de Ucrania afecta a los precios y al volumen negociado de Bitcoin.

1.3.2. *Datos y metodología*

El análisis se extiende desde mayo de 2018 hasta noviembre de 2023 para poder abarcar en su totalidad las noticias relativas a los tres aspectos. En el trabajo se han integrado datos procedentes de varias fuentes de información.

El análisis se estructura en varias etapas. En primer lugar, construimos una base de noticias a partir de Proquest, que permite la selección a partir de términos específicos estableciendo la condición de que las noticias seleccionadas no estén simultáneamente identificadas con otros temas. Hemos seleccionado 3000 noticias que incluían las palabras clave “inflación”, “Covid” y “guerra” publicadas en 100 periódicos relevantes de todo el mundo, 1000 noticias por cada tema. El objetivo de esta primera selección es evitar un alto grado de contaminación con cualquiera de los otros dos temas y garantizar que cada noticia trate principalmente del tema estudiado.

En segundo lugar, con esta información se determinan los días concretos en los que se publicaron estas noticias. Seleccionamos los 100 días con la información más significativa sobre Covid-19, los 100 días con la información más significativa sobre la guerra y los 100 días con la información más significativa sobre la inflación y los consiguientes cambios en el tipo de interés.

Como tercer paso, utilizamos el servicio de datos Bloomberg para extraer todas las noticias de estos 300 días seleccionados, así como su hora, minutos y segundos exactos de publicación (Proquest no proporciona dicha información). Para el periodo analizado, hemos considerado 523 noticias sobre Covid, 71 sobre la guerra entre Rusia y Ucrania y 304 sobre políticas monetarias e inflación.

Además, utilizamos información sobre precios y volumen de Bitcoin con frecuencia horaria, descargados de Cryptodatadownload y calculamos la rentabilidad absoluta cada hora para todo el periodo de estudio. Es esta información por hora la que se utiliza en la primera etapa del análisis empírico.

Finalmente, utilizamos información de alta frecuencia del mercado de bitcoin; en concreto, se han considerado los datos BRTI por segundo proporcionados por el CME como información adicional para ilustrar la reacción de los precios a noticias concretas en algunas fechas relevantes. El BRTI es el índice de referencia que agrega datos de órdenes de los mercados Bitcoin-USD operados por las principales bolsas de criptodivisas. En esta fase, también se amplía el tipo de noticias utilizadas, considerando no solo la selección de información más relevante sino también noticias de menor relevancia de cada uno de los temas propuestos, y también noticias especialmente relevantes sobre temas distintos a Covid, guerra e inflación y tipos de interés.

Todas las bases de datos se han homogeneizado, en caso necesario, a la misma zona horaria, incluso teniendo en cuenta los ajustes del horario de verano.

La metodología se establece en dos fases, un análisis con datos de frecuencia por hora, que nos ofrece una visión a media distancia de los movimientos del Bitcoin, y un análisis con datos de alta frecuencia, que nos ofrece una visión en mayor detalle.

En la primera etapa se trata de observar cómo reacciona el Bitcoin ante la llegada de noticias utilizando precios de cada hora. El modelo estimado tiene como variable dependiente el cambio en la rentabilidad absoluta en una hora. Dada la dificultad de clasificar una noticia como positiva o negativa, nuestro trabajo examina el impacto de la publicación de la noticia en la rentabilidad absoluta. Estudiar directamente el impacto sobre la rentabilidad supondría tener que clasificar una noticia como positiva o negativa, lo que implica un importante grado de subjetividad.

También es necesario reconocer la dificultad de tal clasificación en un momento dado, cuando es imposible aislar una noticia de sus expectativas o de otras noticias que hayan podido publicarse anteriormente. Por eso hemos optado por analizar el impacto en los rendimientos absolutos como medida de los movimientos realizados por los inversores, tanto al alza como a la baja.

Como variables independientes se incluyen los retardos de la variable dependiente necesarios para corregir la autocorrelación de la serie y se añaden tres variables ficticias relacionadas con el momento de publicación de una noticia sobre Covid, inflación o guerra, respectivamente. Además, se incluyen dichas variables ficticias adelantadas y retardadas con el fin de comprobar cuánto dura la reacción a una noticia y cuánto tiempo puede ser anticipada por el mercado. Para la estimación utilizamos modelos de volatilidad condicional, en concreto, un GARCH(1,1).

Dado que la variable dependiente es la variación de la rentabilidad absoluta, un coeficiente positivo (negativo) significativo significa que el anuncio de la noticia está asociado a un aumento (disminución) de la rentabilidad absoluta en comparación con la hora anterior. La interpretación está relacionada con la magnitud de la rentabilidad y es una medida de la incertidumbre de los inversores, similar a la volatilidad. Es decir, si la magnitud de la rentabilidad aumenta (tanto en el caso de subidas como de bajadas de precios), se encuentran coeficientes positivos y significativos, y viceversa.

Para complementar la información proporcionada por los rendimientos absolutos, examinamos el posible impacto sobre el volumen de negociación. El modelo estimado es similar al planteado para la rentabilidad siendo ahora la variable dependiente el cambio en el volumen de negociación, medido como número de Bitcoins, negociado en la hora concreta.

En la segunda etapa se trata de observar la reacción de los precios de Bitcoin a la información, utilizando el CME BRTI segundo a segundo. Este análisis es computacionalmente intensivo y técnicamente difícil de trabajar con los más de 176 millones de datos por segundo que abarca el periodo 2018-2023. Por este motivo, hemos seleccionado unas fechas críticas para cada tema de las noticias y hemos considerado todas las noticias relevantes y no relevantes (aunque importantes a un segundo nivel) proporcionadas por Bloomberg relacionadas con el tema clave correspondiente y las noticias más relevantes sobre otros temas distintos a los del estudio.

Como días representativos de noticias significativas sobre Covid se han elegido los días 11, 12 y 13 de marzo de 2020, contando con un total de 91 noticias y 258.964 rentabilidades absolutas por segundo. Los días 15, 16 y 17 de marzo de 2022 han sido seleccionados como días relevantes para las noticias sobre política monetaria, lo que supone un total de 54 noticias y 259.200 rentabilidades absolutas por segundo. Por último, se han elegido los días 23, 24 y 25 de febrero de 2022 como días clave en el contexto de la invasión rusa de Ucrania, un total de 95 noticias y 259.200 rentabilidades absolutas por segundo.

Para evaluar el impacto de noticias concretas, nos centramos en el estudio de las rentabilidades absolutas utilizando la prueba t para comparar rentabilidades medias antes y después de la publicación formal de la noticia, teniendo en cuenta el segundo exacto en el que se da a conocer la noticia. Para ser coherentes con el propósito de detectar el impacto en los precios, sólo consideramos diferencias en la media inferiores a cero, ya que es representativa de cambios de precios más altos después de la publicación, pero más bajos antes de la publicación. Este hecho supone que la publicación de información origina un cambio significativo en los precios que no existía antes y, por lo tanto, la rentabilidad absoluta después de la publicación es superior a la rentabilidad absoluta antes de la publicación. En esta fase, evitamos las diferencias de medias superiores a cero que podrían identificarse con la anticipación de noticias, ya que nuestro propósito es detectar cuándo se procesa la información.

Para analizar las diferencias en los rendimientos absolutos antes y después de la publicación de una noticia, proponemos dos estrategias diferentes. En la primera, fijamos el intervalo en 30 minutos antes de la publicación y tomamos diferentes intervalos de tiempo después de la publicación (5, 10, 15, 30, 45, 60, 90, 120, 150, 180, 210 y 240 minutos). Para mayor robustez, en la segunda estrategia tomamos diferentes intervalos de tiempo antes de la publicación de la noticia y fijamos 30 minutos después de la publicación. El tiempo de publicación se mide en horas, minutos y segundos según la zona horaria de Chicago, ya que hemos considerado las series temporales de precios de Bitcoin proporcionadas por el índice BRTI.

1.3.3. Resultados y conclusiones

Los resultados obtenidos en la primera etapa, con datos hora a hora, indican que toda la información sobre Covid, inflación o guerra es anticipada por el mercado bitcoin antes de su publicación. A pesar de este resultado común, en cada tipo de noticia se observa un patrón diferente. En el caso de las noticias relacionadas con Covid, la información se anticipa hasta dos horas antes de la publicación y se acentúa hasta la hora de publicación, después el efecto desaparece tras la publicación. Las noticias relacionadas con la guerra también se anticipan dos horas antes de la publicación, pero el efecto se mantiene en la hora de publicación. Por último, las noticias relacionadas con la inflación afectan a los precios del Bitcoin inmediatamente alrededor de la hora de publicación.

En consonancia con los resultados para los rendimientos absolutos, observamos un aumento significativo del volumen de negociación dos horas antes de la llegada formal de la noticia, lo que confirma la anticipación del mercado en los precios, corrigiéndose el impacto a partir de entonces. Hasta el momento de la publicación, las noticias sobre la inflación tienen un impacto significativo en el volumen de negociación.

Hay que tener en cuenta que los tres tipos de noticias son diferentes. Covid-19 es una crisis sanitaria mundial que afecta directamente al bienestar de las personas y a las infraestructuras de salud pública, lo que suscita una preocupación y una urgencia generalizadas. Del mismo modo, la invasión rusa ha perturbado los mercados energéticos, provocando una subida de los precios en todo el mundo, y la información se centra en los acontecimientos militares, los esfuerzos diplomáticos y las consecuencias humanitarias. Estas noticias tienen un impacto personal sobre los individuos. Por el contrario, las noticias sobre la inflación tienden a centrarse en los indicadores y las políticas económicas, influyendo en los mercados financieros, las operaciones comerciales y el poder adquisitivo de los consumidores. Los bancos centrales controlan periódicamente la inflación y ajustan los tipos de interés para estabilizar las economías. Esta periodicidad probablemente hace que el impacto sea más visible alrededor del momento de la publicación.

La segunda etapa del trabajo examina el impacto real que un acontecimiento concreto tiene en los precios del Bitcoin tras su publicación formal con datos segundo a segundo. El análisis de las diferencias medias en los rendimientos absolutos nos permite detectar si se han producido cambios significativos en los precios después de la publicación (con diferencias medias significativas inferiores a cero), comparando los cambios medios en los precios inmediatamente antes de la publicación de la noticia y el periodo inmediatamente posterior a la publicación. Los resultados a lo largo de los distintos intervalos de tiempo nos permiten cuantificar la duración del efecto y la sensibilidad de los resultados a los intervalos de tiempo.

Los resultados indican que la información publicada sobre Covid tiene un claro impacto en los precios de Bitcoin y que este impacto puede durar algunas horas, lo que permite a los inversores en Bitcoin anticipar otra información futura. En resumen, el efecto de anticipación detectado con datos por hora puede deberse al impacto previo de algunas noticias ya publicadas, lo que, a su vez, ayuda a prever la información venidera. Estos resultados sugieren la pertinencia de elegir los intervalos de tiempo adecuados para el análisis. Basándonos en nuestro análisis de los datos horarios relacionados con las noticias de Covid, concluimos inicialmente que las noticias se anticipan. Sin embargo, cuando examinamos los datos segundo a segundo, descubrimos que las noticias tienen un rápido impacto en el momento y también pueden ayudar a anticipar información futura. La secuencia de noticias publicadas anteriormente ayuda a construir inferencias y expectativas sobre lo que ocurrirá en el futuro.

En cuanto a los resultados del impacto de las noticias sobre la guerra se observa que las noticias relevantes tardan al menos dos horas en producir impacto significativo. Al contrario de lo que ocurre con las noticias sobre Covid, otras noticias relacionadas con la guerra también tienen un efecto rápido significativo en los precios, ya que las reacciones se detectan poco después de su publicación. Por lo tanto, parece razonable pensar que estas otras informaciones provocan la anticipación de futuras informaciones relevantes detectadas con datos por hora. En cuanto al impacto de las noticias no relacionadas con la guerra en estos días, se observa que sí tienen impacto, pero al cabo de al menos 30 minutos. Esto sugiere que, durante estos días, la reacción a las noticias relacionadas con la guerra es más importante que la reacción respecto a otros temas.

En el caso de la inflación y la información sobre los tipos de interés, se observa que, en las noticias relevantes, la reacción a la información publicada es casi inmediata y no dura mucho tiempo, en línea con los resultados obtenidos con datos por hora. La reacción de los precios se concentra alrededor de la hora de publicación. Otras noticias no relacionadas con la inflación que se producen en esos días también repercuten en los minutos siguientes, aunque no se observa la inmediatez de las noticias relevantes para la inflación, y el porcentaje de noticias influyentes es aún menor que en el caso de la inflación.

El análisis con datos segundo a segundo nos obliga a ser prudentes respecto a las conclusiones del análisis por hora, permitiendo ajustar algunas afirmaciones anteriores, especialmente sobre el impacto de las noticias tras su publicación. Hemos observado que las noticias importantes sobre Covid o la guerra pueden tardar hasta dos horas en ser procesadas, mientras que las noticias programadas, como las relacionadas con la inflación, tienen menos impacto inmediato. Además, otras noticias pueden tener distintos grados de impacto y duración según su contenido, lo que influye en los resultados si se excluyen del análisis. Nuestra investigación confirma que es difícil determinar el impacto exacto de una noticia debido a la información relacionada que puede generar expectativas sobre futuras noticias. Cuando la reacción a una noticia coincide con otra, resulta complicado separar sus efectos. Es fundamental manejar la frecuencia temporal de los datos con precisión para evitar ocultar los efectos reales de una serie de noticias debido a su cercanía. Es crucial seguir identificando las noticias relevantes para los inversores, ya que son éstas las que afectan a los mercados. Este estudio demuestra que aún hay mucho por aprender sobre los mecanismos de información que influyen en los mercados.

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2. Conclusiones generales

La presente tesis doctoral explora diversos aspectos relacionados con la formación y el comportamiento de las principales variables financieras asociadas a la negociación del Bitcoin. A través de un riguroso análisis, se presentan tres capítulos con un objetivo común: desentrañar algunos de los motivos subyacentes que influyen en la fluctuación de las principales variables de esta moneda (precio, volatilidad y volumen)

A continuación. se describen las principales conclusiones obtenidas en los tres capítulos empíricos.

En nuestro primer capítulo "*Is there an expiration effect in the Bitcoin market?*", se estudia el efecto del vencimiento mensual de los futuros en los mercados de Bitcoin. Se analiza el comportamiento en precios, volumen y rentabilidad de siete importantes bolsas de Bitcoin (Bitstamp, Coinbase, Itbit, Kraken, Gemini, Binance y Bitfinex) en los momentos de vencimiento de tres mercados de futuros regulados (CME, CBOE y Bakkt). Estos mercados de futuros regulados presentan diferentes especificaciones de contratos, sistemas de liquidación y fechas de expiración, lo que permite una exploración exhaustiva del efecto objeto de estudio.

Nuestros resultados muestran que en torno al momento del vencimiento se producen cambios significativos en el volumen de negociación, la volatilidad y la rentabilidad del Bitcoin. Por lo tanto, existe un claro efecto vencimiento relacionado con los futuros sobre esta criptomoneda.

El efecto predominante se encuentra en el volumen de negociación, que aumenta significativamente antes de la fecha de expiración, especialmente en el vencimiento de los contratos de futuros que se liquidan en efectivo, y disminuye después. El patrón de volatilidad es similar, pero más concentrado. Los efectos en rentabilidad, en cambio, no siguen un patrón tan general. De hecho, el único efecto vencimiento claro se detecta por los vencimientos del CME.

Es más, las fechas de expiración de los futuros de CME son las que causan los efectos más notables. Este resultado puede deberse no solo al mayor volumen de negociación en este mercado, sino también al hecho de que el CME es el mercado con más tiempo de permanencia en nuestro horizonte de análisis. En este punto cabe recordar que durante la segunda mitad de 2020 muchos inversores institucionales anunciaron o recomendaron tomas de posición en Bitcoin, lo que contribuyó sustancialmente al aumento del interés abierto (*open interest*) del CME.

Los cambios en volumen y volatilidad son perceptibles algunas horas antes del comienzo del efecto en los precios. Cabe destacar que los mercados (*exchanges*) al contado operan 24/7 en todo el mundo, pero algunos de ellos concentran cuotas significativas de mercado de una zona específica. Por ejemplo, Binance y Bitfinex son mercados fuertes en Asia, Bitstamp y Kraken son mercados principales para clientes europeos, y Gemini, Coinbase y Kraken son actualmente los principales exchanges en EE. UU. La negociación continuada a lo largo de diferentes zonas horarias puede ayudar a explicar la extensión de los efectos en el volumen que, a su vez, pueden inducir efectos posteriores en la volatilidad y los precios.

La fragmentación de los mercados al contado también nos permite detectar algunas diferencias entre *exchanges*. Por ejemplo, en cuanto a los efectos en volumen, grandes mercados como Binance se ven menos afectados que mercados relativamente pequeños como Itbit o Coinbase, que es una plataforma más orientada al consumidor minorista. Desde otra perspectiva, Gemini, con una operativa específicamente ligada a los futuros de CBOE, muestra algunas diferencias en los efectos en las rentabilidades y el volumen en comparación con otras bolsas.

Cabe destacar que el uso de datos intradía proporciona eficiencia al análisis y permite detectar la persistencia de los cambios en las variables del mercado a lo largo del día de vencimiento o en el día anterior o posterior, sabiendo que el efecto no dura más de 24 horas. Asimismo, el análisis de *exchanges* individuales y contratos de futuros con características diversas es especialmente útil para desvelar efectos y resultados significativos que podrían pasar desapercibidos en un estudio más global.

Creemos que esta investigación arroja luz sobre algunas anomalías que ponen en duda la eficiencia del mercado y sobre cómo puede establecerse la fijación de precios de Bitcoin. Los reguladores deben ser conscientes de la fragmentación del mercado. Si se detecta un efecto vencimiento, puede haber anomalías explotables de las cuales algunos participantes pueden sacar ventaja. La evidencia empírica puede ayudar a determinar las áreas donde se requiere mayor acción regulatoria o supervisión.

En el segundo capítulo "*The witching week of herding on Bitcoin exchanges*" se analiza el efecto *herding* (comportamiento gregario) entre las bolsas de Bitcoin (Bitstamp, Coinbase, itBit, Kraken and Gemini, como *exchanges* constituyentes de la referencia BRR del CME y Binance y Bitfinex por cuestiones de volumen), en un momento muy concreto: en torno al vencimiento de los futuros del Bitcoin negociados en el CME.

Utilizando datos intradía y un modelo incondicional confirmamos, en promedio, un comportamiento *anti-herding* para el periodo analizado. Sin embargo, nuestros resultados van un paso más allá al mostrar que en determinados momentos, en los que el descubrimiento de estrategias y la sobrecarga de información son características clave, el *herding* puede aparecer si los inversores encuentran dificultades a la hora de procesar la información para generar sus expectativas. En resumen, encontramos un fuerte efecto gregario antes del vencimiento y unas horas después del mismo. En concreto, estos efectos se extienden a lo largo de la semana anterior al vencimiento (semana bruja) y desaparecen rápidamente el día después del vencimiento.

Los resultados sugieren que, en general, los precios del Bitcoin reflejan la propia información de los inversores, pero, sobre todo, en la semana de vencimiento de los futuros del Bitcoin, este punto es cuestionable, ya que los inversores parecen vigilarse estrechamente unos a otros. Si el efecto gregario es evidente durante la semana de vencimiento, el flujo de información puede no ser tan informativo y podría estar contaminado.

En general, las consecuencias directas del *herding* para los inversores financieros se producen de dos maneras. Por un lado, el *herding* dificulta la diversificación de las carteras de inversión y, por otro, los activos financieros pueden estar mal valorados debido a presiones sobre los precios que aumentan la volatilidad y la inestabilidad del mercado y que, por tanto, pueden alejar los precios de sus valores esperados. En nuestro trabajo, la primera consecuencia no tiene grandes implicaciones para los inversores relevantes, ya que analizamos el *herding* que se produce entre bolsas que negocian el mismo activo, Bitcoin. Sin embargo, la fijación de precios erróneos puede afectar a todos los inversores en todos los *exchanges* en el momento del vencimiento, con la excepción de los tenedores de Bitcoin (*hodlers*), cuyo objetivo son las ganancias a largo plazo.

En las fechas de vencimiento, los inversores son conscientes de la gran cantidad de información que puede influir en la toma de decisiones. Por este motivo, muchos inversores desinformados pueden encontrar útil imitar las decisiones de otros, trasladando esa imitación a las distintas bolsas en las que se negocia el Bitcoin. El *herding* entre bolsas puede amplificar los precios erróneos del Bitcoin, ya que la imitación se propaga a través de diferentes mercados y plataformas. En consecuencia, los agentes del mercado no podrán predecir adecuadamente los precios y pueden encontrarse con niveles de volatilidad que intensifiquen el riesgo asumido.

Nuestros resultados son especialmente importantes para los participantes en el mercado que actúen como arbitrajistas o coberturistas apostando en diferentes bolsas de Bitcoin, ya que las posibilidades de obtener beneficios estarán más limitadas. Los operadores de arbitraje que participan en operaciones de arbitraje triangular (que consisten en detectar las diferencias de precio entre tres criptodivisas distintas) deberían revisar sus estrategias en relación con el Bitcoin, mientras que los inversores de cobertura y arbitraje que operan tanto en el mercado al contado como en el de futuros deberían revisar sus ratios de cobertura.

En nuestro último capítulo, "*Some of the ingredients spicing up the bitcoin price: Covid, inflation and war*" se ha explorado la dinámica de las reacciones del precio del Bitcoin a los comunicados de prensa. Específicamente, nos centramos en tres eventos clave que ocurrieron durante el período de análisis 2018-2023: la pandemia de Covid, la guerra de Ucrania-Rusia y la inflación y el consiguiente incremento de los tipos de interés. Para lograr nuestro objetivo, hemos dividido el trabajo en dos fases. La primera fase implica examinar el patrón de precios con una frecuencia intradiaria por hora, que podemos denominar "visión de distancia media". La segunda fase consiste en examinar el comportamiento de los precios en detalle (segundo a segundo), lo que podemos llamar la "visión de lupa".

Inicialmente, los resultados obtenidos al examinar el impacto de una noticia relevante sobre los temas elegidos con datos por hora indican que las noticias sobre Covid y la guerra se anticipan en los mercados, provocando grandes fluctuaciones de precios, probablemente debido a la incertidumbre que entrañan. Sin embargo, una vez difundida la noticia, el impacto no parece mantenerse. En el caso de las noticias sobre la inflación, el impacto se concentra en torno al momento de la publicación.

Sin embargo, el análisis realizado con datos segundo a segundo nos hace ser cautos sobre las conclusiones extraídas del análisis por hora. Los resultados utilizando esta nueva frecuencia temporal nos permite matizar algunas de las afirmaciones anteriores, especialmente en lo que se refiere al no impacto de las noticias una vez publicadas. En concreto, hemos observado que las noticias relevantes sobre Covid o la guerra tardan hasta dos horas en procesarse tras su publicación, mientras que las noticias programadas con una fecha concreta, como la publicación de la inflación o de la subida de tipos de interés, tienen menos impacto en el tiempo. Además, otras noticias, relevantes o no, pueden tener distintos grados de impacto y duración según el tema, por lo que excluirlas del análisis puede influir en los resultados obtenidos.

Nuestra investigación ha confirmado que es difícil determinar el impacto específico de una noticia cuando existe información relacionada que puede crear expectativas sobre noticias futuras. Además, cuando la reacción a una noticia coincide con la publicación de la siguiente, puede resultar difícil aislar sus efectos. Por lo tanto, es esencial ser precisos en la frecuencia temporal de los datos para evitar enmascarar los verdaderos efectos de una secuencia de noticias debido a la proximidad de la publicación de otras noticias. También creemos que es importante seguir avanzando en la identificación de las noticias verdaderamente relevantes para los inversores, ya que son éstas las que mueven los mercados. Este trabajo demuestra que aún queda mucho camino por recorrer para comprender adecuadamente los mecanismos de información que afectan a los mercados.

En resumen, a través de un riguroso examen de datos y metodologías, hemos profundizado en aspectos clave del mercado de Bitcoin, desde su comportamiento durante el vencimiento de los futuros asociados a esta criptomoneda, analizando también el efecto *herding* en dicho momento y estudiando la influencia de factores informativos externos como la publicación de noticias relevantes. Tal como se ponía de manifiesto en la motivación de la tesis, hemos intentando aunar la necesidad del análisis fundamental a la hora de estimar los precios de los activos financieros y la necesidad de tener en cuenta los sesgos de comportamiento de los inversores, especialmente en el ámbito de las criptomonedas. Nuestros resultados, hasta el momento, revelan especialmente el componente de *behavioral finance* en el mercado de Bitcoin. La existencia de un efecto vencimiento induce a pensar en ineficiencias del mercado, la presencia de comportamiento imitador se relaciona directamente con sesgos cognitivos y/o emocionales, y la dificultad para aislar el impacto de una noticia, junto con el hecho de que una noticia puede ser anticipada por otras noticias previas, limitan notablemente el reconocimiento del tradicional concepto de eficiencia de los mercados en el mercado de Bitcoin.

Aunque queda mucho por aprender respecto a cómo se determinan los precios del Bitcoin, los resultados obtenidos a lo largo de esta investigación no solo contribuyen al entendimiento de la dinámica del Bitcoin, sino que también proporcionan una base sólida para futuros estudios en este campo, ofreciendo perspectivas que pueden resultar útiles para inversores, reguladores y profesionales del mercado.

Con este trabajo, aspiramos a contribuir de manera significativa al conocimiento existente, y que pueda inspirar a nuevas investigaciones en el contexto de las criptomonedas y los mercados financieros digitales.