Commercial Mortgage Distress during the COVID-19 Pandemic: Evalulating the Impact of Government Aid and Mobility*

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Abstract

This paper investigates how government aid and mobility affected the financial distress of commercial mortgages during the COVID-19 pandemic by utilizing data disclosed within asset-backed security monthly performance reports. Government aid is captured through county-level measures of uptake activity for the Payment Protection Program (PPP) and Economic Injury and Disaster (EIDL) loans. A measure of mobility is also measured at the county-level, specifically by using Bureau data on daily transportation. Analysis of how these factors affected distress during the pandemic is also broken down by property type to investigate heterogeneity across different industries. Main findings for PPP uptake activity indicate that higher levels of funding appear to flow to counties more adversely affected by the pandemic, particularly in the case of retail and lodging properties, but it does not play a significant role in reducing loan distress overall. Across different property types, there does seem to be a benefit of PPP for office and mixed-use properties, but results are mixed. On the other hand, EIDL activity is found to correspond with lower loan distress during the pandemic, notably for multi-family and office properties. This provides some evidence about the efficacy of a loan program that is aimed at supporting operating costs rather than payroll. Finally, results for shifts in within-county population mobility during the pandemic period provides evidence that loan distress of commercial mortgages are adversely impacted by declines in travel during the pandemic, notably for retail, lodging, and office properties. This often contrasts pre-pandemic effects and is more impactful than county unemployment rates in many model estimations. Together, these findings are applicable to policy-makers and researchers evaluating the transmission of government policies during the pandemic and with those concerned with ongoing credit risk factors in the commercial real estate market.

Keywords: commercial mortgages, COVID-19, distress, PPP, EIDL, mobility

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1 Introduction

The COVID-19 pandemic has had a momentous effect on economic stability worldwide and within the United States. The speed and severity of the health crisis created widespread uncertainty that quickly roiled markets, prompting record high unemployment rates and asset price volatility. Declaration of a national emergency in the U.S. on March 16$^{\text{th}}$, 2020 caused many local governments to enact restrictions on social interactions and non-essential business activity. The announcement was also quickly followed by an unprecedented wave of fiscal and monetary stimulus intended to address the virus' adverse affects on individuals and businesses country-wide.

This paper seeks to investigate how COVID-19 factors impacted distress within commercial mortgages, an innate part of financing within the pervasive commercial real estate (CRE) market. Publicly available loan performance data across a variety of common CRE property types is obtained that provides a suitable time period of analysis from 2019−2020. Generally, the pandemic has caused a notable increase in distress among commercial mortgages, but this trend is shown to have substantial variation across property types. Three different definitions for loan distress are utilized to explore the robustness of certain results. The two COVID-19 factors of focus for analysis are: PPP activity and mobility. Each are considered at the county-level. PPP activity is broken down into two different measures, Funding Coverage and Loan Coverage, to address both the magnitude and spread of the program in a given county. The measure for mobility is derived from counts of trips that are ≥25 miles in order to capture trends in travel that are not highly localized and routine.

The three main findings of this paper are the following: 1) PPP funding coverage is found to be positively related to loan distress across different model specifications, most consistently for retail and lodging properties.[1] This provides evidence that the magnitude of the program's activity was higher in counties more adversely affected by the pandemic via various measures of distress. It does not imply that funding from the program helped to alleviate distress. Only one instance is found where funding coverage reduces likelihood of distress for multi-family properties. This could allude to the government program being more impactful on residential debt, which would provide multi-family mortgage cash flows, than larger commercial properties. Coverage of PPP loans is not found to have any discernible impact on reduced or increased distress.[2] In the few instances of statistically significant, the small size of the resulting coefficient is conclude to have minimal economic relevance. 2) Increased mobility during the pandemic period is found to be associated with lower likelihood of distress across a variety of property types, especially retail, lodging, and office. Similar results regarding the distress-alleviating effects of local mobility are also found for multi-family and mixed-used properties within some model specifications. These findings stress the sensitivity of large commercial businesses to local travel, a dynamic affected greatly by consumer decision-making and government policy during the pandemic.

The approach of this paper is most closely related to Agrawal et al (2020). What are the major differences? Different data source, difference time-varying characteristics. Different perspective on PPP activity, adding in an additional variable for magnitude of funding. Completely added EIDL as an additional factor that is closely related to supporting business rent and other expenses. Agrawal did not address this program.

Results of this paper are pertinent to a variety of industries. They add to a burgeoning body of academic literature concerned with the efficacy of the PPP program on employment levels and survival of local businesses. As the pandemic persists, policy-makers will need to have granular insight as to what

[1] PPP Fundings Coverage is defined generally as the cumulative amount of PPP funds approved in a county, divided by the number of businesses in the county. See Section 5 for details on variable construction.

[2] PPP Loan Coverage is defined generally as the cumulative number of PPP loans approved in a county, divided by the number of businesses in the county. See Section 5 for details on variable construction.

government programs were most effective for a variety of business types and sizes. Findings also present local mobility statistics as another determinant of CRE credit risk that could useful for many financial institutions that monitor individual loans or the large CMBS market. Scott (2020) emphasizes that debt within the CRE market could be a concerning systemic risk with about 39%, or $1 trillion, of CRE loans being held within bank portfolios.[3] Understanding what local economic factors in the post-pandemic era cause deterioration in the performance of commercial mortgages could thus be important in supporting the stability of the entire U.S. banking industry.

The remainder of this paper is organized as follows: Section 2 provides background information on both the COVID-19 pandemic and the commercial mortgage market that could be useful to the reader. Section 3 briefly discusses the data, methodology, and conclusions of selected academic research that is considered to be in conversation with the findings of this paper. Section 4 reviews sources of data and Section 5 details variable construction and the econometric model for analysis. Section 6 describes all relevant results and Section 7 provides concluding remarks. All tables and figures are included at the end of the paper after the References section.

2 Background

The following two sections are intended to provide the reader a synopsis of the COVID-19 pandemic's current history, notable U.S. policy response, and the commercial mortgage industry, with a particular focus on commercial mortgage-backed securities (CMBS).[4]

2.1 The COVID-19 Pandemic & U.S. Policy Response

The Coronavirus Disease 2019 (SARS-CoV-2 or COVID-19) was initially reported by the World Health Organization (WHO) on December 31$^{\text{st}}$ 2019, with the first recorded cases presumably originating in the city of Wuhan, Hubei province of China. The virus is known now to potentially have adverse effects on patients' respiratory tracks and initial investigation regarded cases as "pneumonia of an unknown cause." While the actual origins remain uncertain, consensus centers around the virus initially being spread from bats, where exposure to the human population would have most likely occurred within "wet" seafood markets within Wuhan. Human coronoaviruses are not an atypical, but the Centers for Disease Control and Prevention (CDC) notes that most animal coronaviruses are rarely infectious to humans. While COVID-19 has many similarities to the outbreak of SARS-COV in 2003, it is also regarded as "novel" for being a new disease not previously recorded in humans. It became increasingly clear to the WHO in late January 2020 of the virus' efficacy to spread quickly amongst humans and the first recorded virus death occured in Wuhan on January 11$^{\text{th}}$, 2020.

The virus continued to spread and receive increased attention in February and January, but a world-wide response remained muted to what was still being considered an epidemic. In the United States, the first recorded case was confirmed to have come from a man returning from Wuhan to Washington State. Most policy in the U.S. at this time was focused on airport screening. The situation intensified in early February, when the U.S. formally declared a public health emergency and began restricting travel from China. A few other counties imposed similar response measures at the time with worldwide spread of roughly about 10,000 cases. By mid-February, the number of deaths reported in China had already surpassed the previous SARS crisis from almost 20 years earlier (AJMC 2021). As total COVID-19 cases

[3] Another 15% of the total CRE loan market is also held by life insurance companies.

[4] For the sake of brevity and scope, most details included are intended to be within the context of this paper's focus. Discussion of the larger, international pandemic response and many U.S. government aid programs are omitted.

reached roughly 100K, the WHO made an assessment on March 11$^{\text{th}}$, 2020 to officially characterize the disease as a pandemic.[5]

National emergency in the United States was declared soon thereafter on March 13$^{\text{th}}$, 2020. Over the next week, states began to issue stay-at-home orders and implement unprecedented nation-wide shutdowns for nonessential businesses.[6] In mid March, a robust combination of fiscal and monetary stimulus was unleashed to address the crisis that began to unfold. The Federal Reserve quickly reduced short term interest rates to 0-25 bps and accounced increased "quantitative easing," which entailed large-scale purchases of treasuries and MBS.[7] This financing activity has rapidly increased the size of the Fed balance sheet to new all-time highs. While policy was record-breaking compared to the Great Recession, it is difficult to argue that the economic conditions of the U.S. at the time did not call for extreme action. One rapid impact of the crisis on labor markets was a 10.6% percentage point spike in unemployment from February and April 2020 (Bartik et al. 2020).[8] See the figure below for how unemployment rates have evolved since 2000:

[Figure: National Unemployment Rates (2000-2021)]

The 14.7% peak reached for unemployment was substantially higher than the 10% peak seen during the Great Recession.[9] On March 27th, 2020, the Coronavirus Aid, Relief, and Economic Security Act (CARES) was officially signed into law, providing roughly $2 trillion of funds through numerous programs to support consumer debt, small businesses, health care, and many other groups. It also made available Treasury funding to the Federal Reserve for establishing a host of emergency lending facilities, such as the Commercial Paper Funding Facility (CPFF) or Main Street Lending Program (MSLP).[10]

The most notable aspect of the CARES Act for the purposes of this paper was Section 1102 and the implementation of the Paycheck Protection Program (PPP).[11] The program was to be carried out by the Small Business Administration (SBA) with a fundamental objective to provide loans for eligible small businesses so employees could stay employed and on payroll for about 8 weeks time. Unlike other disaster-oriented loan programs offered by the SBA,[12] PPP loans had the potential to be forgiven if

[5] A *pandemic* refers to a disease outbreak that affects a large number of a population. This contrasts the CDC stating in February that COVID-19 an epidemic, which also refers to a disease that spreads quickly but does not necessarily imply a wide geographic scope to the spread.

[6] For example, California announced a state-wide stay-at-home order on March 19$^{\text{th}}$, 2020 which remains active as of early February 2021.

[7] Mortgage-backed securities (MBS). Both treasury securities (government debt) and MBS are extremely pervasive fixed income markets in the United States. The Fed's buying efforts help to inject liquidity into these markets and serves as another tool to suppress interest rates. The Fed continues to emphasize its policy that interest rates will remain positive, making the cut of the Federal Funds Rate in March a limited tool for monetary stimulus, as rates were already extremely low in early 2020.

[8] This percentage point spike was not seasonally adjusted.

[9] Since April, rates have declined rapidly to roughly 6.3% in January 2021, but still remain about 80% higher than pre-pandemic levels.

[10] Treasury funding enabled these lending facilities to be created as special purpose vehicles (SPVs) to provide credit to businesses and households. Some programs, such as the CPFF, were essentially revivals of programs that had been enacted during the Great Recession in 2008, when illiquidity in commercial paper markets was shown to have disastrous effects on the economy. Other programs, like the MSLP, were originated for the COVID-19 crisis in an effort to provide credit to smaller businesses. In this sense, some of these newer programs undermined the Federal Reserve's nature as "lender to banks"

[11] For brevity, this paper focuses on discusses on discussing the details of the PPP due to their relevance for research focus. The CARES Act itself contained many other programs directed at providing aid to individuals and businesses.

[12] For example, the SBA has also offer Economic Injury Disaster Loans (EIDL) throughout the pandemic. In contrast to PPP, these loans are not forgivable and require collateral to be posted, among many other differences. However, these funds did not have employee retention criteria and were focused on providing funding for working capital to meet financial obligations. The EIDL program has also existed at the SBA prior to the COVID-19 pandemic, mostly supported small

certain requirements for employee retention were met, essentially rendering the program an opportunity to receive government grants. The terms allowing forgiveness issued by the SBA mainly stated that employee and compensation levels must be maintained and at least 60% of the funding received is spent exclusively on payroll costs. These loans were to be originated by roughly 5,500 lenders across the U.S. and had very agreeable terms: no required collateral or personal guarantee, 1% APR, 2-5 year terms, and deferred first payment periods.[13] The size of individual loans were capped at $10 million, but the SBA has issued guidelines that allow some eligible borrowers that already received one loan to apply for a Second Draw PPP Loan. The program is designed specifically to aid small businesses, which the SBA generally defines as those with ≤500 employees at a given location, but actual eligibility can vary greatly depending on industry type and size of revenues.[14]

Overtime, PPP loans have been met with high demand from businesses and the funding itself has been distributed in discrete rounds, or tranches. The official date to submit an application began on April 3rd, 2020 and approved funding from the Treasury for the first round was $350 billion. Many have argued this allocation was inefficiently small and the uptake for first round funding seems have supported this point. According to SBA reports, in less than two weeks, all the available funding had been distributed for roughly 1.66 million individual loans.[15] An additional round of $340 billion in funding was quickly approved in late-April, and by early May, another 2.57 million loans had been originated.[16] In 2020, the PPP officially closed loan approvals on August 8th, 2020. By this time, a total of 5.21 million loans had been approved for businesses worldwide, amounting to about $525 billion in funding. On January 11th, 2021, the program was reopened for new applications after Congress authorized an additional $284 billion in funding as part of a $900 trillion COVID-19 relief bill passed in December 2020.

The PPP has received considerable attention from researchers since its inception. Many economists have soght to evaluate if the program succeeded in bolstering employment, as well as promoting the survival of small businesses themselves (Autor et al. (2020), Bartik et al. (2020), Granja et al. (2020), Chetty et al. (2020), Hubbard & Strain (2020)). Consensus on the program's intended effects remains largely mixed, with researchers utilizing many different sources of data, time-frames, and geographic levels to reach conclusions. Some criticism has been voiced about accessibility and timing issues within the program itself and/or that there is evidence funds flowed to areas less adversely affected by the pandemic (Granja, et al. 2020). The SBA's Inspector General also announced mounting evidence of fraudulent loan activities in 2020, which subsequently initiated an official probe by the Federal Bureau of Investigation into the specific cases. Conversely, many have also argued there are indications that the program bolstered employment in areas that received more PPP volume or specifically within eligible firms (Bartik et al. (2020), Hubbard & Strain (2020), Autor et al. (2020)). Many additional details of the research methodologies that arrived at these often contrasting viewpoints are described further in Section 3, which reviews relevant literature for the context of this paper.

businesses affected by natural disasters like floods and hurricanes.

[13] Lenders for PPP were essentially local banking branches acting on behalf of the SBA. The banks themselves assumed no risk for originating PPP loans.

[14] See the following Size Standards guide provided by the SBA to determine PPP eligibility. There are many details that address how to calculate number of employees, business size with multiple locations, etc. One notable, and controversial, eligible business industry for PPP were many large fast food companies that were able to receive funding due to individual locations meeting necessary criteria.

[15] The SBA first round report for April 3rd - April 16th 2020 records about $342 billion net dollars approved by 4,795 lenders. The overall average loan size was $206K, but the large majority of loans were $150K and under (74.03% of all loans approved).

[16] In contrast to the first round, funding for these loans totaled about $188 billion. Overall average loan size was also small, at around $73K.

2.2 Commercial Mortgages & Securitization

Commercial mortgages are an integral element of the commercial real estate (CRE) market, which is a pervasive aspect of almost any person's everyday lives. CRE encapsulates income-generating properties that people often interact with on a daily basis, such as offices, malls, and hotels (Scott 2020). To operate a commercial property, businesses can elect to finance themselves with a mortgage, which is not entirely dissimilar from the residential mortgage market. Loans usually involve amortizing principal and interest payments and are often collalaterized by liens on the property they are supporting. However, there are many key differences that distinguish the universe of CRE from the residential market.[17]

Commercial mortgages typically have terms at origination of roughly 5-10 years, while the principal of the loan has significantly slower amortization schedule. This means that the loans often do not fully amortize at the end of the contract period, so the borrower makes a large final payment of principal at the end of the term, popularly referred to as a *balloon payment*. Because the loans often support relatively large commercial enterprises, their typical size can be $10-$20 million, and rarely fall below $1 million. This contrasts a typical residential mortgage with a 30 year term that fully amortizes over the life of the loan. CRE debt also often requires relatively high down-payments (∼20%), leading to loan-to-value (LTV) ratios of 65-75%, and loans tend to be "locked out" from prepayment for 10 years.[18] This implies that prepayment risk is typically extremely low with commercial mortgages, but this is largely counterbalanced with increased risk of default (Fabozzi 2005).[19]

This paper's usage of commercial mortgage data is sourced from commercial mortgage-backed securities (CMBS), which are financial assets that involve packaging a portfolio of CRE debt to serve as the underlying cash flow for investors. This act of structured finance is well-established aspect of U.S. capital markets, with the practice first beginning with the securitization of residential mortgages in the early 1980s. The underlying economic inventive was to take relatively illiquid individual loans, and combine pools of loans into new products that effectively diversify risk, offer stable returns to investors, and increase credit availability to consumers (Clancy et al. 2015). The CMBS market took shape initially in the 1990s, and in 2019, private-label CMBS composed roughly 13.5% (or $466 billion) of the overall $3.46 trillion U.S. commercial and multifamily real estate market (Forte et al. 2019).

The loans within CMBS are referred to as *conduits*, which are typically originated jointly by a group of large lenders, such as commercial and investment banks. Unlike a *porfolio* loan, which is kept within an originator's investment portfolio, conduit lenders intend to sell theirs loans to a depositor, or the intermediary party that coordinates a CMBS transaction (Chang 2020). Loans would be secured by a senior, or first position, lien on the underlying property.[20] For some CRE borrowers, conduit loans can also have desirable terms, like lower interest rates and higher LTVs than portfolio loans. For a visual illustration on a typical CMBS deal structure, see the image below sourced from Forte et al. (2019):

[Figure: CMBS Structure with Features and Parties]

The hierarchical, tranched structure of CMBS is commonplace in almost every type of ABS sector. Each tranche can essentially be considered an individual bond, or certificate, that investors purchase to

[17] It is also possible for some commercial mortgags to be interest-only over the life of the loan.

[18] Often, commercial mortgages have prepayment penalties that would disincentives a borrower from exercising their option to redeem their debt early. This is a major difference between residential mortgages, where prepayment risk and modelling continues to play a central role in origination and securitization of mortgage-backed securities (MBS).

[19] This contrasts residential mortgages and residential mortgage-backed securities (RMBS) where prepayment risk is the predominant concern for pricing and trading.

[20] A first position lien implies that the lender would have priority to claim the property serving as collateral in the instance of a liquidation. With all else being equal, a higher lien position would imply lower credit risk to the lender.

receive the mortgage payment cash flows that channel through the structure of the security.[21] Higher tranche seniority generally implies an investor is entitled to cash flows before subordinate tranches, but consequently receives a lower return on their certificate to compensate for this reduced risk. Generally, the financial engineering of tranches enables new types of securities to be synthesized from the underlying assets that would cater to investor preferences for future cash flows, such average life, duration, credit risk, and many other relevant factors. Many investors, like pension funds or insurance companies, purchase ABS for stable rates of return or for liability-matching strategies.

The entirety of CMBS deals is too detailed of a subject to outline within this synopsis, but two important parties in the CMBS structure in the context of this paper are the *master servicer* and *special servicer*. The master servicer is an entity responsible for collecting monthly payments from borrowers and actively monitoring status of individual loans.[22] If some financial covenant[23] is broken, or a trigger event occurs, the borrower would transferred to the special servicer. This party would then be responsible for taking various action to evaluate borrower distress and potentially enact some kind of workout agreement. This can sometimes involve loan modifications, but the special servicer must be conscious of the certificate holders, whose yields would be highly sensitive to changes in the underlying loan pool. Within this paper, the act of special servicing transferal is utilized as one indicator of commercial mortgage distress for analysis. See Section 5.1 in the methodology for a more detailed description of how the variable is constructed.

3 Review of Literature

3.1 On COVID-19 Policy

Spiegel & Tookes create a novel database of granular, county-level COVID-19 policies to evaluate their effect on future growths in death rates. Their analysis spans a large number of various specifications: stay-a-home orders, mandatory mask requirements, businesses closures, and many others. Their findings suggest some policies consistently predict future reductions in death rates, while others appear to have counterproductive effects. They also address endogeneity concerns by focusing on less populous counties and conducting difference-in-difference studies with counties that neighbor eachother across state borders.

Granja, et al. (2020) study to PPP disburshment by regional banks, local employment support, and business savings from the loans. They utilize micro-data on PPP origination provided by the SBA, employment data from Homebase, and Call Reports for bank financials. They present three main findings with the first being that local banks played a significant role as the intermediaries for PPP origination. Regions with higher exposure to banks received higher levels of lending and also received funds more quickly. Studying the program's effect employment, they only find a modest positive impact that rules out any large employment effects in short term. However, they caveat marginal improvement in employments by their findings that PPP funding appears to promoting financial stability. Firms that had greater exposure to the program were more likely to make various scheduled payments.

Li & Strahan (2020) investigate how banking relationships affected the supply and impacts of PPP loans, drawing some parallels to Granja, et al. (2020). They point out that while PPP loans present

[21] Many types of ABS have often been called *pass-throughs*, describing how the principal and interest of the underlying loans are distributed via the security to certificate holders.

[22] Chang (2020) also note that there can also be a *primary* servicer that works in conjunction with master service. This entity is usually contracted to manage borrower interactions on behalf of the master servicer.

[23] A *financial convenient* describes certain rules established in a debt agreement that are essentially promises a borrower makes to its lender. Typical covenants are usually financial ratios the borrower must not reach or fall below, ex: EBITDA / debt. Often, covenants will stipulate how much debt, or leverage, a borrower is allowed to take on.

no credit risk exposure to local banking entities, heterogeneity in banking relationships strongly predict PPP supply. This is most likely due to a bank's economic interest in the survival of its most familiar borrowers. Sources for data focus on Call Reports and county-level statistics sourced from Track the Recovery. Results suggest that the signifiance of banking relationships in PPP distribution is evidence for inefficiency in the program, because it undermines merit based on distress from the pandemic. They also find areas with higher PPP lending, reflective of pre-pandemic relationship dynamics, lowered local unemployment during the crisis.

Bartik et al. (2020) analyze the collapse of the labor market at the onset of the pandemic using data from Homebase, Current Employment Statistics (CES), and their own personal surveys of workers. Their measure for PPP volume is calculated as the amount of small-dollar loans awarded to businesses in Homebase's primary sectors of retail and food services.[24] At the state level, they concluded that higher levels of PPP volume implied lower probabilities of stopping work in April and higher probabilities of starting work in May or June.

Autor et al. (2020) have released a preliminary paper evaluating the PPP using administrative payroll data from Automatic Data Procressing (ADP) at the micro-level. This enables them to employ a granular, high-frequency difference-in-difference event study specification that estimates the relationship between PPP eligibility and employment levels. The authors make a note to emphasize that their study contrasts Granja et al. (2020) and Bartik et al. (2020), as they were examining effects at the firm-level rather than state or county-level. Their results indicate that PPP did have a significant employment boost at eligible firms by 2-4.5% through the first week of June, which they emphasize to be a evidence for a casual effect of PPP on aggregate employment.

Chetty et al. released an elaborate paper describing how they created publicly available database to track the economic affects of COVID-19 and subsequently performed a variety of their own analyses, including an evaluation of the PPP program on increased employment. Regularly updated statistics for the database are made available at the Opportunity Insight's Economic Tracker. Overall, they found that loans received by small businesses through PPP had only a small effect on employment rates and that cost per job saved by PPP was $377,000. They postulated that this could be evidence that loans flowed to many firms who were not planning to lay off many of their employees due to the pandemic. The modest results also suggest that such types of government programs are quite expensive for the benefits produced, however, they emphasize their paper does not address potential long term benefits of PPP that have yet to be fully realized.

Hubbart & Strain (2020) utilize data from the Dun & Bradstreet Corporation to perform a series of event studies and difference-in-difference analyses on the overall success of the PPP program in support small business health. While they emphasize their limited time window is too early to asset any definitive conclusions on the PPP as a whole, their results do suggest that the PPP increased employment levels, financial health, and business survival.

3.2 On Commercial Mortgage-Backed Securities

Agarwal, et al. (2021) is perhaps most applicable to the focuses of this paper. Acquiring detailed CMBS performance data from Trepp, they sought to determine if PPP coverage at a given county-level helped to alleviate loan delinquencies. PPP coverge specifically refers to the number of loans approved in a county, divided by the number of businesses in that county. Their sampling of commercial mortgages is also broken down by loan size, with the motivation being that smaller sized loans could have a larger

[24] Bartik et al. (2020) also prsent another measure of PPP activity that ranks states by total volume of PPP funds awarded, divided by total state payroll.

percentage of small businesses. Their results show that higher PPP coverage did translate to lower delinquency levels in small mortgages, with the most prominent benefits being for retail properties.[25] They also document heterogeneity of effects between different funding rounds, finding that the second round was more effective than the first. This aligns with other research that has pointed out that the efficiency of PPP fund allocation for the most adversely affected businesses improved after the first round.

Academic research specifically discussing COVID-19 and distress within commercial mortgages still remains somewhat sparse. However, research conducted by various rating agencies and CMBS data providers has been prolific during the pandemic, such as Moody's and Kroll Bond Rating Agency (KBRA), and Trepp. These firms are responsible for closely monitoring changes in CMBS and loan-level performance, often for the purposes of making timely upgrades or downgrades to credit ratings.

4 Data

All sources of data utilized for analysis are detailed in the subsections below. For convenience, readers may also refer to Section 8.1 where a summary table of data sources is provided.

4.1 Commercial Mortgage Performance

Commercial mortgage performance data is obtained from Finsight Group Inc., who directly scrapes monthly reporting files given by publicly listed CMBS security servicers to the U.S. Securities and Exchange Commission (SEC) in accordance with Reg AB II.[26] This regulation came into effect in late 2016 and required new, detailed asset-level disclosure for commercial mortgages and a variety of other consumer ABS, such as auto loans and leasing. The reporting files specifically are referred to as Form ABS-EE (Electronic Exhibits) and differ from *tear sheets* that have traditionally been included within security prospectuses as additional transparency for investors. These sheets would have typically provided pool-level information about the status of underlying loans and collateral at the time of security issuance. In contrast, ABS-EE provide granular updates on a variety of relevant loan-level information that investors can access on the monthly basis, notably: property type, property location, and delinquency status.

The data collected includes securities issued from November 2016 - February 2020, with the beginning of the time frame corresponding to when Reg AB II was officially passed on November 23$^{\text{th}}$, 2016.[27] The sample also ends before March 2020, such that it only includes loans that were originated and securitized prior to the pandemic taking shape in the United States. Accordingly, each loan in the sample has at least one pre-pandemic observation. Given this time period, the sample contains reporting from a total of 163 individual CMBS securities from a variety of originators. The sample is then first cleaned to include only loans securitized by a single property.[28] A similar methodology for cleaning was implemented by Furfine (2020). Thereafter, the sample is cleaned further to include the six most prominent property types for analysis: retail, office, lodging, multi-family, mixed-used, and industrial.[29]

[25] Agarwal et al. (2020) arrive at a definition for "small mortgages" by considering quintiles within their own data.

[26] Commercial mortgages within these securities are by nature *conduit*, rather than portfolio. Data can be found specifically on EDGAR within a given security's filing platform. Finsight tracks all relevant CMBS securities on EDGAR and then scraps the reported XML files and converts them to a user-friendly CSV format.

[27] See the following link for additional details on Reg AB II compliance.

[28] With most CMBS securities, loans securitized by a portfolio are properties usually only compose 5-15% of the total pool of funds. The diversified nature of cash flows for these loans makes them unconducive to utilize with this paper's focus being focused on geographical impacts. A very small percentage of loans were also located within U.S. Territories, like Puerto Rico, or the Cayman Islands. These loans were dropped from the sample.

[29] The industrial property type includes any property specifically defined as industrial or warehouse. Multi-family housing is included as a major type of CRE because the properties are operated by businesses seeking to generate income from their

One specific example of a security contained in the reporting is BNK-2019, issued by Wells Fargo.[30] This is one of many of such securities issued by Wells Fargo. Discuss the property make-up of the security. Discuss that most loans are single property and originated close to securitization date. Delinquency status at origination is commonly muted and develops as the security gets older.

Property addresses for individual commercial mortgages are provided at the zip code level. To convert these zip codes to a county-level, the most recent update released by HUD's Office of Policy Development and Research is utilized for its USPS Zip Code Crosswalks.[31] The methodology for mapping using the file are important to note due to the fact that zip codes, used by the U.S. postal service, do not necessarily correspond on a one-to-one basis with county FIPS codes.[32] To address this phenomena, this paper utilized population density data provided within the Crosswalk file that indicated what percentage of a population[33] was within each sub-section of a zip code that corresponded to multiple counties. From this data, it was most common that one zip-county combination contained +90% of the total zip population. Accordingly, in any instance of non-unique zip-county combinations, a given zip code was mapped to the county in which it has the highest population density.

The final data set is an unbalanced panel of 5,901 unique loans and with 125,142 monthly observations spanning from January 2019 - December 2020 . A table of summary statistics for the entire sample is provided in Section 9.2. The average interest rate and original loan amount are 4.67% and $18.81M. Most loans have terms of 10 years, or 120 months, with the maximum term being 20 years. Average remaining term on a loan, a time-variant characteristic, is around 96 months, which suggest that most loans observed are relatively young. Finally, the average loan-to-value ratio is 53%, which is typical for commercial loans but low compared to residential mortgages and other consumer debt.[34]

4.2 Unemployment Rates

Monthly unemployment rates at the county-level are acquired from the Bureau of Labor Statistics (BLS) for the entire duration of the loan sample.[35] See the figure below that illustrates unemployment rates in some large counties relative to the national average since the beginning of 2019:

[Figure: County & National Unemployment Rates (2019 - 2020)]

Most county-level rates seem to correspond closely with the national level before the pandemic struck the country in April, hovering around 3-5%. During the pandemic period, there seems to be more noise with county rates with most having receded from their peaks to around 5-10% as of December 2020. Table 2 in Section 8.1 also provides summary statistics of unemployment rates within the sample. The average rate is roughly 6.27%, which is not surprising considering the sample is relatively evenly balanced between the pre- and post-pandemic period.

residents (Scott 2020). Examples of other property types in securities that were dropped includes: cooperative housing, self-storage, mobile home, and health care. Overall, these properties only composed a very small percentage of the total sample and thus were not included in analysis.

[30] See here for the security's filings with the SEC.

[31] The most recently released file is for Q4 2020.

[32] Federal Information Processing Standards (FIPS). An individual zip code can be associated with multiple counties in some instances.

[33] This percentage encapsulates both residential and business density as measured by the HUD.

[34] High down payments for commercial property can cause market LTVs to be low compared to residential mortgages, where LTVs are commonly 60-80%. This would assume a typical homeowner down-payment of 20% or more. In stark contrast, LTVs for auto loans, another prevalent piece of consumer debt, can often exceed 100% LTV.

[35] This data was also utilities by Agrawal et. al (2020).

4.3 Mobility Statistics

Measures of county-level mobility are procured from the Bureau of Transportation Statistics, specifically its regularly updated Trips by Distance report that was first released at the beginning of 2019.[36] It is composed of a variety of travel statistics generated by monitoring an anonymized, national panel of mobile devices. The BTS emphasis that appropriate weighting procedures are utilized to expand their samples and produce results that are representative of an entire population in a nation, state, or county.

Trips being measured within the data are defined as any movements that involve a stay of longer than ten minutes at some anonymized location away from a device user's residence, which are updated on weekly basis. At a more granular level, the BTS provides daily trip counts in a county that is broken down by the length of the trip. The lowest bin is <1 miles and the highest is ≥ 500 miles. The notion of a trip encapsulates all forms of transportation: driving, rail, transit, and air. If a movement includes multiple stay periods, then it is recorded as multiple trips. At the most generalized level, the BTS provides a variable called *Population Staying at Home*, that is the number of residents in a given county who made no trips with a trip ending more than one mile away from their home.

4.4 PPP Loans

Loan-level origination data for the entire PPP is obtained from the Small Business Administration (SBA) and provides extremely granular information data on all PPP loans that have been approved since the program opened in early April 2020. A number of useful characteristics about loan and borrower are provided, notably the borrower's zip code and approved loan amount. It is important to note that this data has been updated since December 1$^{\text{st}}$, 2020 to include exact loan amounts greater than 150K, and the names of smaller borrowers. This information was omitted in the initial release of the PPP data potentially utilized by researchers who published papers in the summer of 2020.[37] An extremely small number of loans are dropped from analysis due to missing zip codes or loan amounts. The same mapping process that was discussed in Section 4.1 was utilized for converting PPP loan zips to the county level.

5 Methodology

This section outlines first how both dependent and independent variables are generated from the data described in the previous section. An econometric model is then proposed to address how measures of loan distress could have been affected by mobility and government aid programs, if at all.

5.1 Defining Commercial Mortgage Distress

To create indicators of loan distress from reporting data, this paper generates three different measures: default, special servicing transferal, and delinquency transition. These variables are not mutually exclusive and are intended to address difficult types of distress that could be relevant to both policy decision and investors.

Mortgage **default** ($\mathbb{D}$) is an indicator that marks any loan that has become ≥ 30 days delinquent in a given month. The term *default* in finance can potentially have many different definitions and thresholds in practice. This paper utilizes the term to describe a borrower that has breached their contractual late

[36] The data itself is estimated for the BTS by the Maryland Transportation Institute and the Center for Advanced Transportation Technology Laboratory at the University of Maryland.

[37] See the following Wall Street Journal article regarding the second released of more detailed SBA data. Many news organizations filed lawsuits in an effort to know more about loan recipients that had been omitted in the original report.

period and failed to make scheduled payments on their loan. The ≥30 day threshold is a popular in academic research and with many firms that build CMBS credit risk indices. The figure below illustrates the evolution of default rates overtime within the sample data, broken down by property type:

[Figure: Commercial Mortgage Default Rates]

Prior to the pandemic, it appears that all default rates were around 1-2% and exhibited by little volatility.[38] After the April reporting period, the month when most policies took effect, default clearly surged for most property types. Lodging default rates peaked at approximately 25% and have remained above 20% since May 2020. Peak default for mixed use, retail, and multi-family were also about 8%, 6%, and 4.5% respectively. Industrial properties' default rates appear the least adversely affected by pandemic. Most rates have also declined since their peaks in the summer of 2020, but still seem the largely remain above pre-pandemic levels. These trends align relatively well with the larger CMBS sample employed by Agrawal et al. (2020). They also report exceptionally high lodging default rates around 25%.

A mortgage involved in **special servicing** ($\mathbb{S}$) is an indicator that flags any loan that is listed as having been transferred to a special servicer for the entirety, or portion of, a reporting period. This measure of distress reflects active monitoring from the master servicer of borrowers in a CMBS security's portfolio, where a transfer could occur before any actual indications of delinquency or default are recorded. See below for the evolution of special servicing rates overtime:

[Figure: Commercial Mortgage Special Servicing Rates]

Similar to default rates, the pandemic appears to have catalyzed a surge in special servicing across many different property types. However, these rates do not show any marked signs of decline overtime since April 2020, with many property types currently at their historical peaks. Lodging appears to be a notable outlier again, with its rate of special servicing reaching about 24% of the loan pool.[39]

A mortgage undergoing a **delinquency transition** ($\mathbb{T}$) is an indicator variable for loans that are flagged if they have progressed to a higher stage of delinquency in a given reporting period. Within the performance data, loan delinquency is given at discrete intervals rather than a continuous measure of days or months. Examples could be transitioning from 30→60 days or 60→90 days delinquent. This measure also includes loans that have shifted from current to late status.[40] Delinquency transition rates overtime are shown in the figure below:

[Figure: Commercial Mortgage Delinquency Transition Rates]

In contrast to default and special servicing, transition rates appear to have more volatility before the crisis and stronger declines since their peaks during the pandemic period. Like the previous two measures, lodging is the most affected property type with peak transition rates reaching +30% in May 2020. Most property types also experienced peak levels of delinquency transition during the summer months of 2020, when most social and business restrictions were in full effect.

5.2 Time-Variant Loan Characteristics

Remaining-term, most recent DSCR, and most recent occupancy. Occupancy would signal tenant density and degree of overall tenant diversification, which could relate to stability of cash flows. A property with

[38] Generally, the term *volatility* is used in the context of finance to describe a standard deviation within historical data, typically returns on a security or index.

[39] Agarwal et al. (2020) also utilize a special servicing measure as an additional indicator of loan distress in their own robustness checks.

[40] A loan marked as *late* is specifically defined as any loan that has missed a scheduled payment, but is still less than 30 days delinquent.

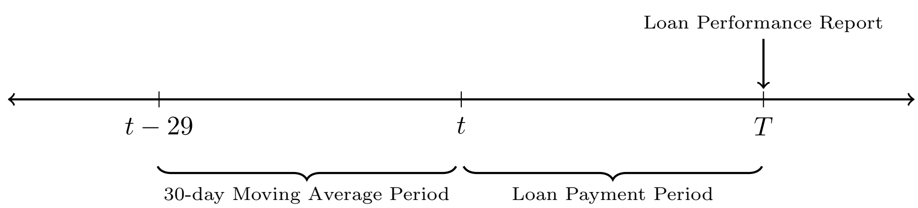
low, or declining, occupancy could experience a reduction in rent cash flow, resulting in higher distress. A property that consistently has a low occupancy could also be most susciple to a economic crisis, where it would could be highly dependent on a small number of tenants to not default on their rent.

The debt-service-coverage-ratio (DSCR) refers to specifically to a property's monthly net operating income, divided by its monthly debt payment. A population credit metric, synonymous to a mortgage debt-to-income (DTI) ratio.

There are other time-variant charasteritics that are not considered in this paper. Agrawal uses a contract-spread and a approximation for loan to value. While having a current-loan-to-value ratio would be relevant, the inconsistency in reporting current loan balances within the data makes this extremely difficult to implement. Sometimes, a current loan balance is simply stated as the original loan amount. This is definitely a notable consideration to be made for future research with this data.

5.3 Mobility

Using the BTS daily data, this paper generates a measure for mobility as a 30-day moving average of daily trips in a given county that are ≥25 miles, divided by the county population in 2019.[41] The variable is referred to as *mobility* within analysis, but can be literally considered a *trips per capita* measure for a given county. The ≥25 mile threshold is intended to focus on transportation that would be most closely related with longer-distance trips for leisure, commuting, air-travel, and other instances for travel that would not be locally constrained. Additionally, the threshold could also be a reasonable proxy for capturing cross-county or cross-state travel activity. The specific period for the moving average are the 29 days that proceed a CMBS security reporting period (which then also includes the day of reporting). This time frame is intended to capture the recent trend in mobility within a county. Intuitively, it transforms daily statistics into a lagged monthly measure of mobility. The diagram below illustrates how this average would correspond to the loan payment period and actual date of a loan performance report:



In the diagram, t represents the reporting period beginning date of a particular CMBS security for its ABS-EE filing and T represents the reporting period ending date for the same security. The time span $T - t$ is roughly 30-days (1 month) for all loans in the sample. A moving average is constructed by considering the 30 days proceeding a reporting period start date for a given commercial mortgage, inclusive of the day the reporting period begins, which corresponds to the time span from $t - 29$ to t. The calculated average is a *simple moving average* (SMA) which implies each day's measure is weighted by the number of periods in the average, i.e. a weight of 1/30 for each day.

With this framework, mobility measures can be generated for each loan in the sample by date and county. Concretely, the formula used to generate the moving-average would be the following:

$$Mobility_{t,c} = \frac{1}{30} \sum_{i=0}^{29} \frac{T_{t-i,c}}{P_c} \tag{1}$$

[41]Estimates of 2019 county populations are sourced from Chetty et al. (2020) and are estimated by the Census Bureau.

$Mobility_{t,c}$	$\sim$	30-day moving average of mobility in time t and county c
$T_{t-i,c}$	$\sim$	Daily count of trips $\geq$25 miles in time $t-i$ and county c
P_c	$\sim$	Census Bureau population estimate for county c in 2019

To illustrate how the moving average measure corresponds to daily variation in mobility,see the following example figure that overlays the variables overtime for Harris County, Texas:[42]

[Figure: Mobility Overtime (Harris County, TX)]

Table 2 in Section 8.2 also provides summary statistics for mobility within the sample. The average value is about 0.21 and median is 0.20, which would imply about 1 in 5 people within a county make a $\geq$25 mile trip each day. This appears to be a reasonable approximation considering that individuals who are not actively working and commuting, like children and the elderly, would probably not be making routine trips of this length.

5.4 PPP and EIDL Activity

This paper seeks to employ a dual perspective for evaluating PPP and EIDL activity. This involves generating two measures of loan uptake activity for the PPP and EIDL, calculated on a daily basis since the start of the program. The first is *Funding Coverage* or *FCov* and is intended to capture the magnitude of loan aid within a county at a given time. It is calculated as the following:

$$FCov_{t,c} = ln\left(1 + \frac{1}{B_c}\sum_{i=\tau}^{t} F_{t,c}\right) \tag{2}$$

$FCov_{t,c}$	$\sim$	Cumulative PPP (or EIDL) funding per business in time t and county c business at time t in county c
$F_{i,c}$	$\sim$	Cumulative PPP (or EIDL) funds at time t in county c
B_c	$\sim$	BLS total business count in county c from Q1 2020

The time period τ represents the first day the program officially opened for loan approval on April 3rd, 2020. The natural log of the ratio is taken such that results from analysis can be interpreted as a "percent change in funding coverage" or a "percent change in funding per business."[43] The second measure is *PPP Loan Coverage*, or *LCov*, and intended to address potential shortfalls with *PPP Funding Coverage*, particularly that it could generate similar results if many small businesses in county requested loans or one sizable business received a loan. Thus, considering funding coverage will address the *spread* of PPP funding, not just magnitude. Concretely, the formula for loan coverage would be:

$$LCov_{t,c} = \frac{1}{B_c}\sum_{i=\tau}^{t} \text{Ł}_{i,c} \tag{3}$$

$LCov_{t,c}$	$\sim$	Cumulative PPP (or EIDL) loans per business in time t and county c
$L_{t,c}$	$\sim$	Cumulative PPP loans at time t and county c
B_c	$\sim$	BLS total business count in county c from Q1 2020

[42] Harris County is considered the third most populous county in the U.S. according to the 2010 census. It is 1,777mi^2 and mostly encapsulates the city of Houston.

[43] An additional +1 (or \$1) is added to each measure such that the measure does not equal \$0 in instances when a county received no funding. Strictly non-zero observations would then enable a natural log to be taken.

Literature that utilizes PPP origination data have proposed a variety of options for measuring its impact on a particular area. Agarwal, et al. (2021) focus specifically on a measure for PPP coverage, which is the ratio of cumulative PPP loans received in a county divided by the number of businesses in the county at a given point in time. Li & Strahan (2020) also have their own measure that uses businesses specifically larger than 500 employees, as indicated by County Business Patterns data released by the BLS. Defining a measure to address business size is a relevant consideration but is not addressed in this paper for the following reasons: most counties are composed of 99% businesses that 500 employees or less. The actual regulations about business size are more flexible according to the SBA, where standards can vary based on industry or total revenue. For these reasons, it seems logical that total businesses is a good proxy for business presence and does not address more subtle rules concerning business eligibility.

Table 2 in Section 8.2 provides summary statistics for both PPP activity variables. Within the sample, average funding coverage was about $54,000 and loan coverage was 46.9%.[44] In the most extreme case, it appears that PPP loan coverage can exceed 100%, which is not necessarily unreasonable considering that some slight discrepancy could arise from using business count estimates from BLS and having to map zip addresses of loans (approximately) to the county-level. The fact that average business coverage is roughly 50% with a county points to the widespread business demand for PPP loans during the pandemic. While the maximum amount for a loan was $10 million, the average funding per business also seems to encapsulate well the fact that the vast majority of loans approved were less than $150K.

5.5 Econometric Model

To investigate how commercial mortgage distress affected by mobility shifts and PPP activity during the pandemic, this paper employs a fixed effects framework (FE) at the loan-level for analysis. The de-meaning process effectively controls for many aspects of loan heterogeneity at origination.[45] Agrawal et al. (2020) also emphasize that loan fixed effects rule out local tendencies or regulations that often can be influential factors in deterring mortgage default. Year-month fixed effects are also included in all regressions that control for that common economic and pandemic-related trends over the course of the sample. Formally, the specification for regression is the following:

$$Y_{i,t,c} = \kappa + \beta A_{t,c} + \lambda(M_{t-1,c} \times C) + \theta M_{t,c} + \phi U_{t,c} + \delta L_{i,t,c} + \alpha_i + \tau_t + \epsilon_{i,t,c} \tag{4}$$

$Y_{i,c,t}$	$\sim$	Binary indicator variable for loan distress for a loan i in time t and county c
$A_{i,t,c}$	$\sim$	Matrix of PPP and EIDL activity measures in time t and county c
$M_{t,c} \times C$	$\sim$	Mobility and COVID-period interaction term
$M_{t,c}$	$\sim$	Mobility in time t and county c
$U_{t,c}$	$\sim$	One-month lagged unemployment rate in time t and county c
$L_{i,t,c}$	$\sim$	Matrix of time-variant loan characteristics for loan i in time t and county c
α_i	$\sim$	Loan-level fixed effects
τ_t	$\sim$	Year-month time fixed effects for the reporting period's beginning month
$\epsilon_{i,t,c}$	$\sim$	Error term

The dependent variable Y represents one of the three measures of mortgage distress described in Section 5.1, specifically: default, special servicing, or delinquency transition. The interaction term $M_{t-1,c} \times C$ is the main variable of focus to determine the effect of mobility on loan distress, conditional on the time

[44] The variable for PPP Funding is summarized before a natural log transformation was applied. For analysis, the variable is used in the natural log format.

[45] Examples of loan characteristics could be: interest rate, loan amount, term, maturity date, original LTV, a ballon payment indicator, and many others.

period being the COVID-19 pandemic.[46] Loan remaining term is included as time-variant variable to address the notion that performance and borrower decision making can be associated with the "seasoning" of the loan itself. Lagged unemployment is also added as another time-variant factor to address contemporaneous economic conditions between counties. This regression model is estimated for the entire sample and across each of the 6 individual property types: retail, office, lodging, mixed-used, multi-family, and industrial. All empirical results are discussed in the next section.

6 Empirical Results

The results of estimating Equation (4) on the different measures of loan distress are discussed in detail below. Given each dependent variable is a binary indicator, a positive coefficient in the model would imply *increased* probability of loan distress, and vice versa. With the models, all coefficients also represent the marginal effect of a unit increase in the independent variable. This effect is a *percentage point* (pp) increase in the dependent variable, which is important to distinguish from a *percent increase*. For PPP Funding Coverage, which was transformed using the natural log, a unit-increase would correspond to a percentage increase. Mobility is also one variable that produces substantially large results from a unit-increase, considering average mobility within a county is about 0.20. To consideration more reasonable marginal effects of mobility, results are discussed as the effect of standard deviation increases rather than a full unit-increase.[47]

6.1 Default, PPP Activity, & Mobility

Table 3 analyzes the link between default ($\mathbb{D}$) and the various independent variables. Within the entire sample, there is a strongly significant, and positive, effect of PPP Funding Coverage. A percentage increase of funding coverage increases probability default by 1.96pp. The benefits of increased mobility on loan distress are also evident in Column (1), where a standard deviation increase reduces likelihood of loan default by 0.94pp. This constrasts the pre-pandemic period, where the effect of mobility was positive, but statistically insignificant. Breaking the sample into each property type, the impact of PPP funding is apparent for retail and lodging properties. A percentage increase in funding coverage increases default probability of a loan by 3.21pp and 17pp respectively. There is also an additional, marginally significant impact of funding coverage on default for mixed-use properties. These results provide initial evidence that PPP support flowed to counties adversely affected by the pandemic, signalled by the defaulting loans in the sample, but present no indication that distress was alleviated. PPP Loan Coverage also does not have any statistically significant relationship with default, suggesting that loan coverage was not a pertinent factor for supporting relatively large commercial loans. These results contrast somewhat with Agarwal et al. (2020), that found positive effects for loan coverage, particularly for smaller sized mortgages.[48]

Mobility is found to be a significant factor in reducing likelihood of distress within office, lodging, and multi-family properties. Specifically, a standard deviation increase reduces likelihood of default in a given month by 0.75pp, 3.23pp, and 1.58pp, respectively. Retail properties also exhibit a marginally significant result that corresponds to a decrease of 1.09pp in probability of default for a standard deviation

[46]Specifically, the COVID-19 period within analysis is defined as any reporting period starting from April 1st, 2020 and afterwards. This enables lagged shifts in independent variables that occurred when the pandemic began in March to be considered part of the pandemic period, which would have affected loan payments during April.

[47]Agrawal et al (2020) also utilized standardized variables in some of their model specifications to discuss results with PPP coverage and refer to this as the *intensive margin* of the PPP.

[48]It is important to note that Agarwal et al. (2020) did not also consider funding within their model specifications.

increase in mobility.[49] Mixed-used property also showed an expected, negative coefficient, but it is not statistically significant. For industrial properties, mobility shifts do not seem a relevant factor on default. Results for mobility during COVID also contrast pre-pandemic coefficients, which are largely insignificant or positive. Surprisingly, unemployment rates do not seem to be particularly impactful across different property types with the exception of lodging; a percentage point increase in unemployment increases likelihood of default by 0.74pp. Results also appear mixed for the impact of a loan's remaining term on default.

6.2 Special Servicing, PPP Activity, & Mobility

Table 4 focuses on special servicing ($\mathbb{S}$) as a dependent variable. Results are relatively similar to Table 3 with mortgage default. In Column (1) with the full sample, PPP Funding Coverage has a positive, but marginally significant, effect on the probability of special servicing. PPP Loan Coverage also has a positive relationship with special servicing likelihood, but the effect is somewhat small. A percentage point increase in loan coverage increases special servicing probability by 0.0648pp, an economically insignificant result compared to other coefficients. The interaction coefficient for mobility is also positive and significant in Column (1), providing further evidence about local travel's connection to financial health of large commercial businesses.

The robustness of the effect of PPP Funding Coverage on increasing distress in retail and lodging properties seems persistent with special servicing as a new measure. A percentage increase in funding coverage increases likelihood of special servicing by 1.6pp and 11.1pp respectively. For the two property types, these coefficients are significant at the 1% level, but are also smaller in magnitude than the increase in likelihood of default from the previous model. In Column (3) with office properties, there is marginally significant evidence that PPP funding reduced likelihood of special service, but this result is complicated by the positive, marginally significant coefficient for PPP loan coverage. Consequently, the predominant evidence still appears to be that it was allocated to distressed areas, but had little role in reducing the loan distress itself. More generally, loan coverage is found one again to have no notable economically or statistically significant effect on loan distress indicators.

A standard deviation increase in mobility decreases likelihood of special servicing by 0.71pp and 2.88pp in office and lodging properties, respectively. Retail property displayed a marginally significant, negative coefficient. Again, this beneficial effect of mobility during COVID period contrasts pre-pandemic effects that were all insignificant or positive. The effect of unemployment is positively significant for lodging and multi-family, increasing likelihood of special servicing by 0.84pp and 0.11pp. There is also a negative and significant coefficient for office properties and unemployment, but the effect is relatively small (-0.089pp).

6.3 Delinquency Transition, PPP Activity, & Mobility

Table 5 investigates the relationship between loan delinquency transition ($\mathbb{T}$) and the independent variables across various property types. Similar to the previous two estimations, PPP funding coverage is positively related to loan distress in Column (1). A percentage increase in funding coverage increases likelihood of delinquency transition by 1.37pp. The mobility interaction term of interest is statistically significant and implies that a standard deviation increase in mobility decreases probability of delinquency transition by 0.46pp. Unemployment rates are not found to be an impactful factor on delinquency transition in the full sample.

[49] The reported t-statistic for this coefficient was 1.83.

The positive effect of PPP funding on distress in retail and lodging properties remains robust when considering delinquency transition. A percentage increase in funding coverage increases likelihood of delinquency transition by 1.6pp and 8.49pp across each property type, respectively. In contrast, for multi-family properties, it is found PPP funding coverage has a *negative* effect on loan distress. A percentage increase implies lower likelihood of delinquency transition by 2.91%. This result is the only evidence that contradicts the notion that the PPP had little impact on reducing commercial loan distress. Since the cash flows underlying a multi-family property are actually sourced from residential borrowers, the result could suggest that the PPP was more impactful for the financial well-being of individual consumers, rather than larger businesses.

The effect of increased mobility during the COVID-19 is found to be significantly distress-reducing for retail and mixed-used properties. A standard deviation increase in mobility reduces likelihood of delinquency transition by 0.91pp and 1.75pp, respectively. Coefficients across other property types, with the exception of industrial, are also negative, but statistically insignificant. Unemployment is only found to have marginally significant and mixed results across various property types.

7 Conclusion

This paper investigated distress of commercial mortgages during the COVID-19 pandemic. Results that indicate that higher PPP funding is associated with loan distress could be most useful for policy makers interested in evaluating the success of allocating funds to adversely affected areas across the country. The effects of mobility would likely be pertinent to professional investors and CRE loan originators that seek to evaluate credit risk determinants. With some demographic shifts caused by the pandemic persisting longer than many had originally expected, the sensitivity of loan distress to mobility during the pandemic era could remain relevant moving forward. Finally, academic research on the CMBS and CRE markets during the pandemic remain seemingly sparse. Given the size and integration of the CRE market into daily life and the banking sector, providing research insights on this topic is paramount as the pandemic continues to persist and the market does not show immediate signs of recovery.

There are many potential concerns for future research in this space. Perhaps most important is that the COVID-19 pandemic continues into 2021 and it is clear that commercial mortgage distress has not abated in any significant way. Many brick-and-mortar outlets were already in decline before the virus struck, and new consumer preferences could accelerate this process drastically. Office space is also a major area of CRE whose future remains uncertain. Many companies seem to be entertaining the notion of a more permanent work-from-home environment. This could put future pressure on mortgage payments if occupancy levels and tenant cash flow are reduced because companies no longer desire the spaces. Multi-family space also remains at risk because so many consumers have received forbearance and stimulus checks for support. Once this support fades, distress in this sector could quickly provoke difficultly with paying the larger mortgage.

Investigating the PPP program is crucial because the program is so novel U.S. policy, is pervasive country-wide, and continues develop into mid-2021, with granular data being released periodically by the SBA. A full, comprehensive view of the PPP efficacy will probably not be achieved for years to come, when research. But it is the hope of this paper that it presented a methodology to evaluate the program, and consider uptake activity from a dual perspective.

EIDL is another topic that is crucial for future study. While it is not new or as large as PPP, but its size is extremely large. It is relevant to small businesses. This program seems to have received less coverage than PPP. This paper sought to bridge the two programs.

There are many additional topics that could potentially be worth covering within the final draft of this paper. Some property types were not covered in analysis, such as: co-operatives, health care, and self-storage. These could be added in a future draft the but the amount of loans available on these properties is somewhat low. More detailed information on the PPP is available, such as how many jobs each loan covered at a given business. PPP activity could also be segmented by industry and loan size. Most research has focused on loan size, but industry support could be another relevant topic. Data is also available on EIDL activity during the pandemic that could be coupled with PPP analysis; this does not seem have been implemented by researchers thus far for the pandemic. Another factor for considering credit risk could be a measurement of industry exposure, specifically the percentage share of a certain business type within a county. All of these considerations will be made in order to produce a final draft that provides the most useful analysis on commercial mortgage distress during the pandemic.

References

[1] Agarwal, Ambrose, Lopez, and Xiao (2021) "Did the Paycheck Protection Program Help Small Businesses? Evidence from Commercial Mortgage-Backed Securities," Available at SSRN: https://ssrn.com/abstract=3674960 or http://dx.doi.org/10.2139/ssrn.3674960

[2] American Journal of Managed Care, or AJMC (2021) "A Timeline of COVID-19 Developments in 2020," Last updated January 1st, 2020. Available at: https://www.ajmc.com/view/a-timeline-of-covid19-developments-in-2020

[3] Alekseev, Amer, Gopal, Kuchler, Schneider, Stroebel, & Wernerfelt (2020) "The Effects of COVID-19 on U.S. Small Businesses: Evidence from Owners, Managers, and Employees," *Working Paper 27833.* Available at: http://www.nber.org/papers/w27833

[4] Autor, Cho, Crane, Goldar, Lutz, Montes, Peterman, Ratner, Villar, & Yildirmaz (2020) "An Evaluation of the Paycheck Protection Program Using Administative Payroll Microdata," *Preliminary* version as of July 22nd, 2020. Available at: http://economics.mit.edu/files/20094

[5] Bachas, Ganong, Noel, Vavra, Wong, Farrel, & Greig (2020) "Initial Impacts of the Pandemic on Consumer Behavior: Evidence from Linked Income, Spending, and Savings Data," NBER Working Paper #27617. Available at: https://www.nber.org/papers/w27617

[6] Barrios, Minnis, Minnis, & Sijthoff (2020) "Assessing the Payroll Protection Program: A Framework and Preliminary Results," Available at SSRN: https://ssrn.com/abstract=3600595

[7] Barrot, Grassi, Sauvagnat, & Julien (2020) "Costs and Benefits of Closing Businesses in a Pandemic," Available at SSRN: https://ssrn.com/abstract=3599482

[8] Bartik, Bertrand, Lin, Rothstein, Unrath (2020) "Measuring the Labor Market at the Onset of the COVID-19 Crisis," NBER Working Paper #27613. Available at: https://www.nber.org/system/files/working˙papers/w27613/w27613.pdf

[9] Chang (2020) "Analysis of Distressed Commercial Mortgaged-Backed Securities (CMBS) Loans and Special Servicing - A Case Study," *Center for Real Estate*, Massachusetts Institute of Technology (MIT). Available at: https://dspace.mit.edu/handle/1721.1/129103

[10] Chetty, Friedman, Hendren, Stepner, & the Opportunity Insights Team (2020) "The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data," September 2020. Available at: https://opportunityinsights.org/wp-content/uploads/2020/05/tracker˙paper.pdf

[11] Clancy, Fabozzi, & McBride (2015) "The Post-Crisis CMBS Market: Will Regulations Prevent Another Market Meltdown?" *The Journal of Portfolio Management.* Special Real Estate Issue. Available at: https://jpm.pm-research.com/content/41/6/118.short

[12] Fabozzi (2005) "The Handbook of Fixed Income Securities," *Seventh Edition.*

[13] Forte, Foster, LaBianca, & Stafford (2019) "Role of CMBs in the Financing of Commercial and Multifamily Real Estate in America," *MBA Commercial Real Estate Finance.* Available at: https://www.mba.org/2019-press-releases/november/cmbs-market-plays-a-significant-role-in-commercial/multifamily-real-estate-finance

[14] Furfine (2020) "The Impact of Risk Retention Regulation on the Underwriting of Securitized Mortgages," *Journal of Financial Services Research,* 58, 91-114. Available at: https://link.springer.com/article/10.1007/s10693-019-00308-6

[15] Goolsbee & Syverson (2020) "Fear, Lockdown, and Diversion: Comparing Drivers of Pandemic Economic Decline 2020," NBER Working Paper #27432. Available at: https://www.nber.org/papers/w27432

[16] Granja, Makridis, Yannelis, & Zwick (2020) "Did the Paycheck Protection Program Hit the Target?" NBER Working Paper #27095. Available at: https://www.nber.org/papers/w27095

[17] Hubbard & Strain (2020) "Has the Paycheck Protection Program Succeeded?" NBER Working Paper #28032. Available at: https://www.nber.org/papers/w28032

[18] Li & Strahan (2020) "Who Supplies PPP Loans (and Does It Matter?)? Banks, Relationships, and the COVID Crisis," NBER Working Paper #28286. Available at: https://www.nber.org/papers/w28286

[19] Santos (2020) "Natural History of COVID-19 and Current Knowledge on Treatment Therapeutic Options," *Elsevier Public Health Emergency Collection.* U.S. National Library of Medicine National Institutes of Health.

[20] Small Business Administration, or SBA (2021) "Paycheck Protection Program Loans: Frequently Asked Questions (FAQs)," Current version as of January 29$^{\text{th}}$, 2021.

[21] Scott (2020) "COVID-19 and the Future of Commercial Real Estate Finance," *Congressional Research Service*. Available at: https://fas.org/sgp/crs/misc/R46572.pdf

[22] Spiegel & Tookes (2020) "Business Restrictions and COVID Fatalities," Available at SSRN: https://ssrn.com/abstract=3725015 or http://dx.doi.org/10.2139/ssrn.3725015

[23] World Health Organization, or WHO (2021) "Listing of WHO's Response to COVID-19," Available at: https://www.who.int/news/item/29-06-2020-covidtimeline

8 Tables

8.1 Summary of Data Sources

Data	Geographic Level	Time Period	Source
CMBS Performance	Loan-level by zip code	January 2019 - January 2021	Finsight Group Inc.
Unemployment Rates	County-level	January 2019 - January 2021	Bureau of Labor Statistics (BLS)
PPP Loan Origination	Loan-level by zip code	April 2020 - February 2021	Small Business Administration (SBA)
EIDL Origination	Loan-level by zip code	April 2020 - February 2021	Small Business Administration (SBA)
Mobility Statistics	County-level	January 2019 - February 2021	Bureau of Transportation Statistics (BTS)
QCEW	County-level	Q1 2020	Bureau of Labor Statistics (BLS)

CMBS Performance files from Finsight Group Inc. are scraped directly from SEC ABS-EE reports. PPP is an abbreviation for the Payment Protection Program and QCEW is the BLS Quarterly Census of Employment and Wages. Data given at the zip code level was mapped to the county-level using the most recent USPS Zip Code Crosswalk file released by the HUD's Office of Policy Development and Research. For additional details on this mapping process, see Section 4. Census Bureau 2019 county population estimates are also sourced from Chetty et al. (2020). Granular details on each field and the relevant variables generated for this paper are included in Section 4 on data sources and Section 5 on methodology.

8.2 Summary Statistics

Table 1: Summary Statistics for Commercial Mortgages

Variables	**N**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Original Interest Rate	130,316	4.671	4.750	0.612	2.298	6.705
Original Loan Amount	130,316	18,825,381.011	12,650,000.000	17,316,340.855	505,879.440	137,260,000.000
Original Loan Term	130,316	116.195	120.000	14.616	59.000	240.000
Remaining Term	130,316	96.105	99.000	20.431	6.000	239.000
Origination Year	130,316	2,017.753	2,018.000	0.996	2,002.000	2,020.000
Securitization Year	130,316	2,017.919	2,018.000	0.953	2,016.000	2,020.000
Original Property Value	130,316	120,847,910.218	21,000,000.000	403,809,841.493	1,175,000.000	4800000000.000
Original LTV	130,316	53.486	61.864	20.606	0.271	94.118
Most Recent DSCR	130,316	2.085	1.930	0.887	0.000	15.820
Most Recent Occupancy	130,316	90.822	95.500	12.590	1.010	100.000
Default ($\mathbb{D}$)	130,316	0.031	0.000	0.173	0.000	1.000
Special Service ($\mathbb{S}$)	130,316	0.028	0.000	0.164	0.000	1.000
Delinquency Transition ($\mathbb{T}$)	130,316	0.033	0.000	0.179	0.000	1.000

Table 2: Summary Statistics for PPP, EIDL, Mobility and Unemployment

	N	Mean	Median	Std. Dev.	Min	Max
PPP Funding Coverage	58319	55,202.581	54,919.715	17,758.533	455.925	110,612.352
PPP Loan Coverage	58319	47.714	50.323	16.833	0.199	111.602
EIDL Funding Coverage	58319	16,821.921	16,991.244	11,497.683	1.000	55,585.684
EIDL Loan Coverage	58319	30.648	29.228	24.272	0.000	156.665
Mobility	130316	0.213	0.199	0.092	0.029	1.174
Unemployment	130316	6.298	4.400	4.365	1.400	34.600

PPP activity statistics are summarized from the beginning at the start of the program on April 3^{rd}, 2020. Before this date, all measures would be effectively equal to zero. The same is applicate for EIDL statistics, where the summary is given since the start of the program for COVID-related funding on April nd, 2020.

9 Empirical Results

9.1 Aggregate

Table 3: Commercial Mortgage Distress, PPP, and Mobility

	(1) $\mathbb{D}$	(2) $\mathbb{D}$	(3) $\mathbb{S}$	(4) $\mathbb{S}$	(5) $\mathbb{T}$	(6) $\mathbb{T}$
PPP Funding Coverage	0.0138**	0.0156***	0.00509	0.00665	0.0121***	0.0126***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
PPP Loan Coverage	0.000836**	0.000815**	0.000900***	0.000882***	0.000234	0.000228
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EIDL Funding Coverage	-0.00487***	-0.00453***	-0.00185*	-0.00156	-0.00555***	-0.00546***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
EIDL Loan Coverage	-0.000352**	-0.000374**	-0.000215	-0.000234	-0.0000290	-0.0000348
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mobility $\times$ COVID	-0.122***	-0.118***	-0.100***	-0.0962***	-0.0550***	-0.0538***
	(0.036)	(0.035)	(0.036)	(0.035)	(0.021)	(0.020)
Mobility	0.0386	0.0289	0.0616	0.0531	-0.0250	-0.0276
	(0.041)	(0.040)	(0.039)	(0.038)	(0.030)	(0.030)
Unemployment	0.00110*	0.00126**	0.000664	0.000807	0.000738*	0.000782*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Remaining Term		-0.000443***		-0.000397***		-0.000206
		(0.000)		(0.000)		(0.000)
Most Recent DSCR		-0.0160***		-0.0139***		-0.00424**
		(0.003)		(0.003)		(0.002)
Most Recent Occupancy		-0.00217***		-0.00193***		-0.000601***
		(0.000)		(0.000)		(0.000)
Constant	-0.0343	0.230***	-0.0147	0.220***	-0.00301	0.0779**
	(0.032)	(0.040)	(0.029)	(0.037)	(0.026)	(0.032)
Observations	130316	130316	130316	130316	130316	130316
R^2	0.375	0.383	0.430	0.437	0.161	0.162
Property Type	All	All	All	All	All	All
Number of Loans	5893	5893	5893	5893	5893	5893
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

(Click here to return to the discussion of this table in the text.)

Robust standard errors clustered at the loan-level are included in parentheses. The dependent variable $\mathbb{D}$ for loan distress is an indicator variable for loans marked as $\geq$30 days delinquent in a given reporting period. COVID FE refer to an added control for new virus tests per 100K at the state-level (results not shown). See Section 4 for details on data sources and Section 5 for methodology. Coefficient asterisks ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

9.2 Property Heterogeneity

Table 4: Commercial Mortgage Default, PPP, and Mobility

	(1) $\mathbb{D}$	(2) $\mathbb{D}$	(3) $\mathbb{D}$	(4) $\mathbb{D}$	(5) $\mathbb{D}$	(6) $\mathbb{D}$
PPP Funding Coverage	0.0314***	-0.00186	0.172***	-0.0198	0.0283*	-0.00471
	(0.008)	(0.005)	(0.028)	(0.013)	(0.015)	(0.011)
PPP Loan Coverage	-0.000216	0.000410	0.000141	0.00106**	-0.000678	-0.000214
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
EIDL Funding Coverage	-0.000725	0.00101	0.00206	-0.00665**	-0.00331	-0.00211
	(0.003)	(0.001)	(0.006)	(0.003)	(0.006)	(0.004)
EIDL Loan Coverage	-0.0000710	-0.0000998	-0.000551	-0.000582**	-0.00000954	0.000290**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Mobility × COVID	-0.0990*	-0.0761**	-0.336***	-0.176**	-0.0414	0.00320
	(0.053)	(0.039)	(0.115)	(0.073)	(0.147)	(0.068)
Mobility	-0.0540	-0.0368	0.118	0.113	-0.252	0.0620*
	(0.050)	(0.046)	(0.140)	(0.069)	(0.207)	(0.035)
Unemployment	0.00164*	0.000298	0.00732***	0.000224	0.00389**	0.000428
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
Remaining Term	-0.000110	-0.000148***	0.0209***	0.00342***	-0.000907***	0.000538
	(0.000)	(0.000)	(0.003)	(0.001)	(0.000)	(0.001)
Most Recent DSCR	-0.0177***	-0.00192*	0.0161**	-0.00312	-0.0141	0.00420
	(0.006)	(0.001)	(0.007)	(0.003)	(0.010)	(0.005)
Most Recent Occupancy	-0.000982*	-0.000239	0.0000527	-0.000614*	-0.00104	-0.000386
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Constant	0.0320	0.0569	-2.764***	-0.140	0.153	-0.00345
	(0.065)	(0.039)	(0.354)	(0.153)	(0.119)	(0.090)
Observations	43762	30555	20977	16907	10522	7593
R^2	0.348	0.364	0.447	0.413	0.357	0.586
Property Type	Retail	Office	Lodging	Multi-Family	Mixed-Use	Industrial
Number of Loans	1944	1375	943	816	477	338
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

(Click here to return to the discussion of this table in the text.)

Robust standard errors clustered at the loan-level are included in parentheses. The dependent variable $\mathbb{D}$ for loan distress is an indicator variable for loans marked as $\geq$30 days delinquent in a given reporting period. COVID FE refer to an added control for new virus tests per 100K at the state-level (results not shown). See Section 4 for details on data sources and Section 5 for methodology. Coefficient asterisks ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5: Commercial Mortgage Special Servicing, PPP, and Mobility

	(1) $\mathbb{S}$	(2) $\mathbb{S}$	(3) $\mathbb{S}$	(4) $\mathbb{S}$	(5) $\mathbb{S}$	(6) $\mathbb{S}$
PPP Funding Coverage	0.0166**	-0.0102**	0.126***	0.00769	0.00907	0.00217
	(0.008)	(0.005)	(0.026)	(0.006)	(0.010)	(0.004)
PPP Loan Coverage	0.000200	0.000612**	-0.000254	0.000418	0.000881	-0.0000303
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
EIDL Funding Coverage	-0.00202	-0.00196**	0.00451	0.000100	-0.00341	0.000448
	(0.002)	(0.001)	(0.005)	(0.001)	(0.003)	(0.000)
EIDL Loan Coverage	0.0000804	-0.0000824	0.0000644	-0.000211	-0.000834*	0.000135
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Mobility $\times$ COVID	-0.118**	-0.0804**	-0.293***	-0.0728	0.112	-0.0112
	(0.060)	(0.040)	(0.113)	(0.062)	(0.141)	(0.023)
Mobility	0.0122	-0.0833	0.213*	0.0248	-0.0539	-0.0100
	(0.056)	(0.052)	(0.127)	(0.065)	(0.169)	(0.011)
Unemployment	0.00110	-0.000782*	0.00791***	0.00133**	0.00282*	0.000378
	(0.001)	(0.000)	(0.002)	(0.001)	(0.002)	(0.000)
Remaining Term	-0.000136	-0.000116**	0.0138***	0.00339***	-0.000430	0.0000791
	(0.000)	(0.000)	(0.004)	(0.001)	(0.000)	(0.000)
Most Recent DSCR	-0.0144**	-0.00225*	0.0230***	-0.00322	-0.0176*	-0.0000816
	(0.007)	(0.001)	(0.008)	(0.003)	(0.010)	(0.004)
Most Recent Occupancy	-0.000836*	-0.000634**	0.00116*	-0.000689	-0.000462	-0.000225
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Constant	0.0678	0.156***	-2.023***	-0.294**	0.0918	0.0110
	(0.065)	(0.046)	(0.351)	(0.115)	(0.113)	(0.032)
Observations	43762	30555	20977	16907	10522	7593
R^2	0.422	0.503	0.465	0.580	0.389	0.861
Property Type	Retail	Office	Lodging	Multi-Family	Mixed-Use	Industrial
Number of Loans	1944	1375	943	816	477	338
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

(Click here to return to the discussion of this table in the text.)

Robust standard errors clustered at the loan-level are included in parentheses. The dependent variable $\mathbb{S}$ for special servicing is an indicator variable for loans that were currently transferred to a special servicer for the entirety, or a portion, of a given reporting period. See Section 4 for details on data sources and Section 5 for methodology. Coefficient asterisks ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 6: Commercial Mortgage Delinquency Transition, PPP, and Mobility

	(1) $\mathbb{T}$	(2) $\mathbb{T}$	(3) $\mathbb{T}$	(4) $\mathbb{T}$	(5) $\mathbb{T}$	(6) $\mathbb{T}$
PPP Funding Coverage	0.0155**	0.00753	0.0854***	-0.0298**	0.0225	-0.00440
	(0.008)	(0.005)	(0.018)	(0.013)	(0.014)	(0.010)
PPP Loan Coverage	0.0000323	-0.0000945	-0.000579	0.000485	-0.000926	0.0000916
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
EIDL Funding Coverage	-0.00460	0.00170	0.00745	-0.00413	0.00324	-0.00634
	(0.004)	(0.002)	(0.007)	(0.004)	(0.008)	(0.005)
EIDL Loan Coverage	0.0000844	-0.0000234	0.00000431	-0.000262	0.0000875	0.000237
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mobility × COVID	-0.0768**	-0.0218	-0.0831	-0.0677	-0.209**	0.0394
	(0.031)	(0.030)	(0.064)	(0.043)	(0.088)	(0.052)
Mobility	-0.0346	-0.128***	0.0395	0.0752*	-0.299	0.0421
	(0.042)	(0.038)	(0.100)	(0.040)	(0.186)	(0.064)
Unemployment	0.00107*	-0.0000484	0.00233	-0.000808	0.000526	-0.0000118
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Remaining Term	-0.0000978	-0.0000644	0.00670***	0.00309**	0.000557	0.000650
	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)
Most Recent DSCR	0.00477	0.00357	-0.0116***	0.00293	-0.00368	-0.00101
	(0.003)	(0.002)	(0.004)	(0.002)	(0.006)	(0.007)
Most Recent Occupancy	-0.000308	-0.000388*	-0.000498	-0.000187	-0.000709	-0.000561
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Constant	0.00883	0.0363	-0.926***	-0.103	0.0120	0.0332
	(0.055)	(0.033)	(0.238)	(0.144)	(0.163)	(0.116)
Observations	43762	30555	20977	16907	10522	7593
R^2	0.146	0.117	0.231	0.146	0.166	0.143
Property Type	Retail	Office	Lodging	Multi-Family	Mixed-Use	Industrial
Number of Loans	1944	1375	943	816	477	338
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

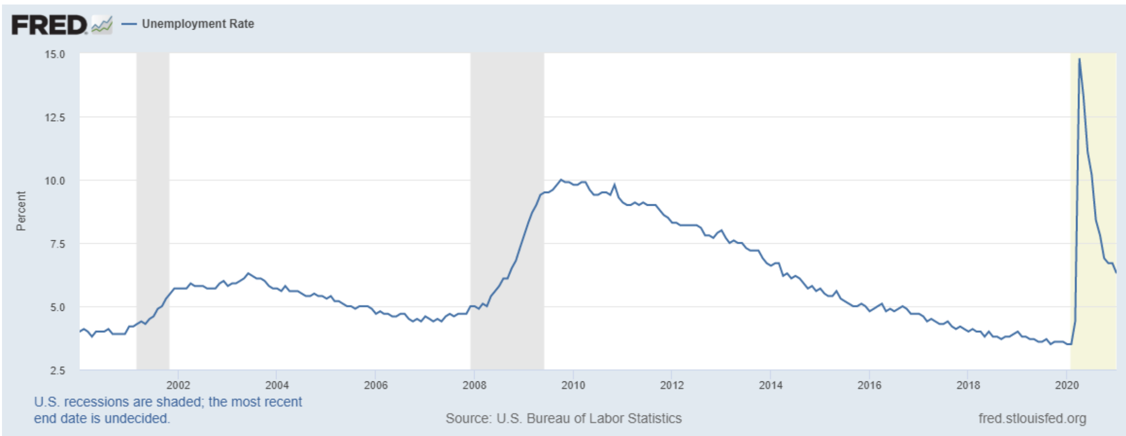
(Click here to return to the discussion of this table in the text.)

Robust standard errors clustered at the loan-level are included in parentheses. The dependent variable $\mathbb{T}$ for delinquency transition is an indicator variable for loans that were marked during periods in which they transitioned to a higher stage of delinquency. See Section 4 for details on data sources and Section 5 for methodology. Coefficient asterisks ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

10 Figures

10.1 National Unemployment Rates (2000-2020)

Figure 1: National Unemployment Rates



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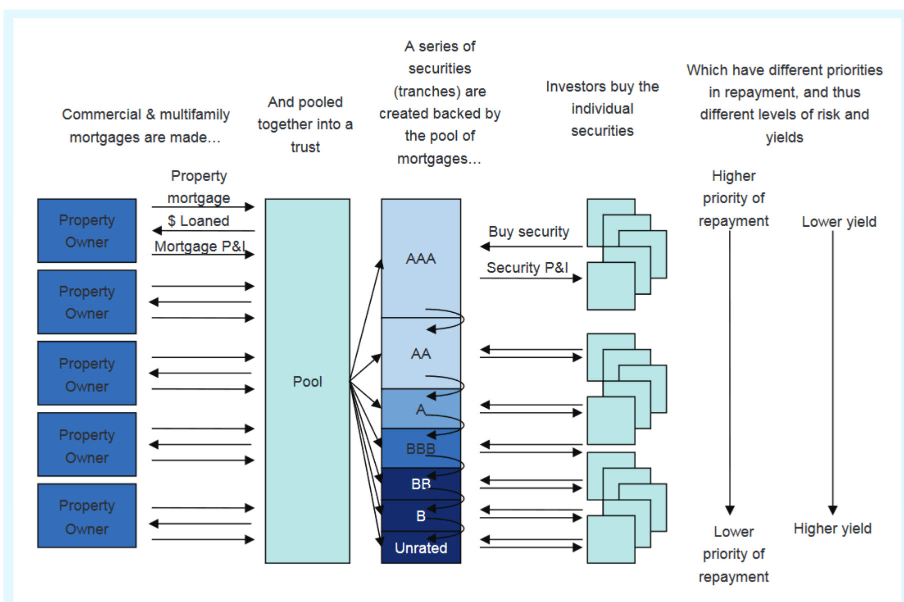
10.2 A Typical CMBS Deal Structure

Figure 2: CMBS Structure with Features and Parties



Source: Forte et al. (2019)

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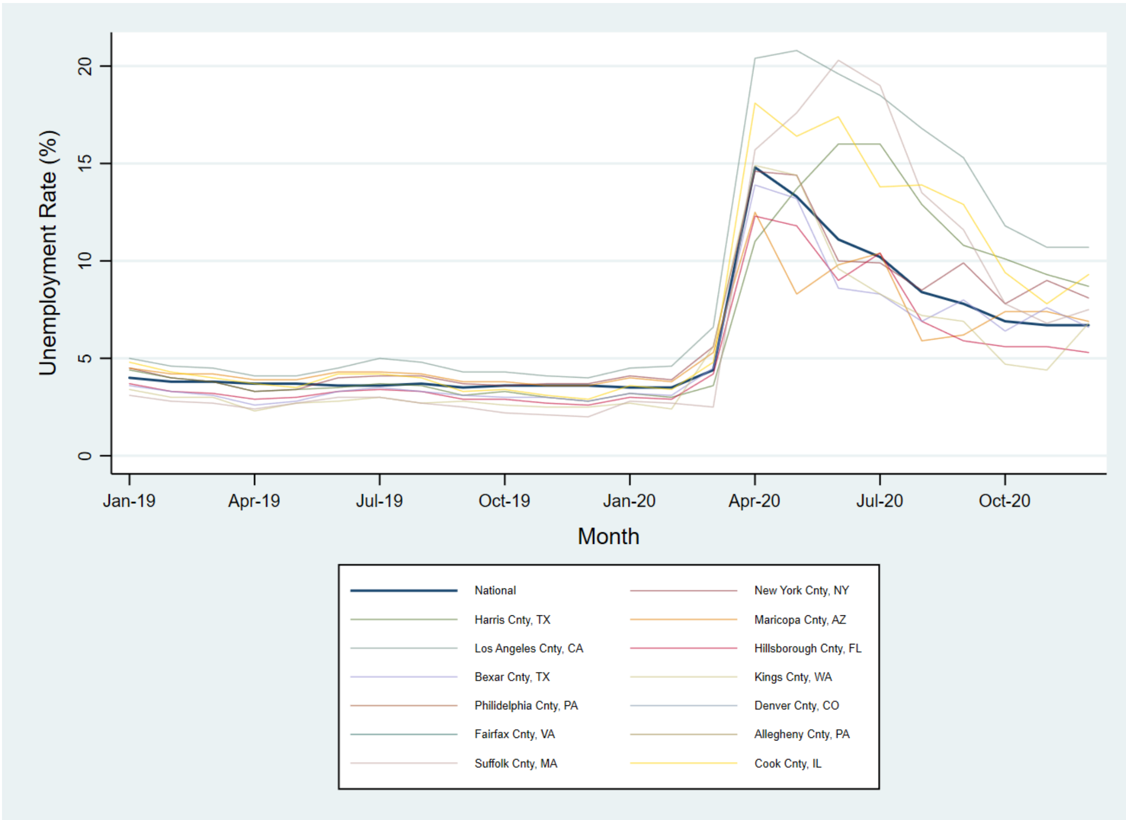
10.3 Unemployment Rates

The national average is shown by the thicker blue line. Some large counties country-wide were arbitrarily selected.

Figure 3: National Unemployment and Select County-Level Rates



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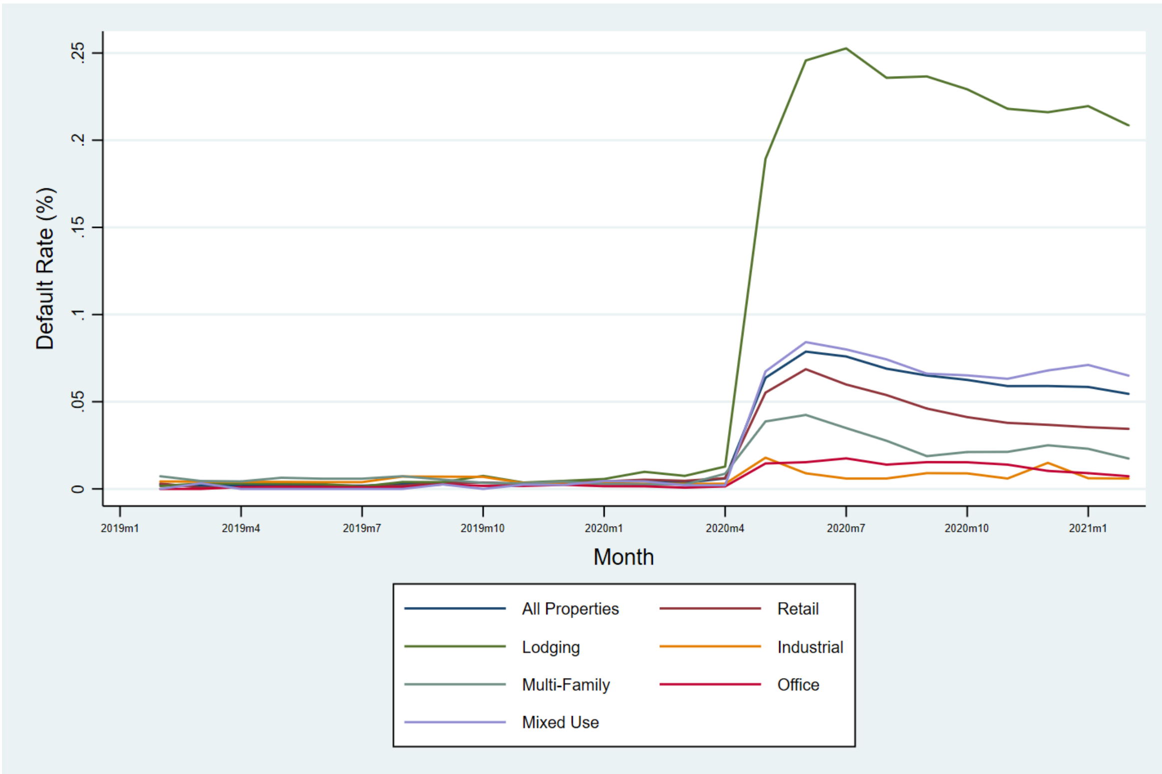
National unemployment rates reached a record high of 14.7% in April, declining since then to about 6.7% in December. This contrasts the pre-pandemic rate of approximately 3.5% that had been declining steadily since the Great Recession. The county unemployment rates featured above appear to exhibit some spread around this national average and it is clear that rates have not dropped below 5% since their surge began during the pandemic in March 2020.

10.4 Commercial Mortgage Default

These figures are generated from the paper's sample of commercial mortgages and also segmented by major property types.

Figure 4: Commercial Mortgage Default ($\mathbb{D}$) Rates by Property Type



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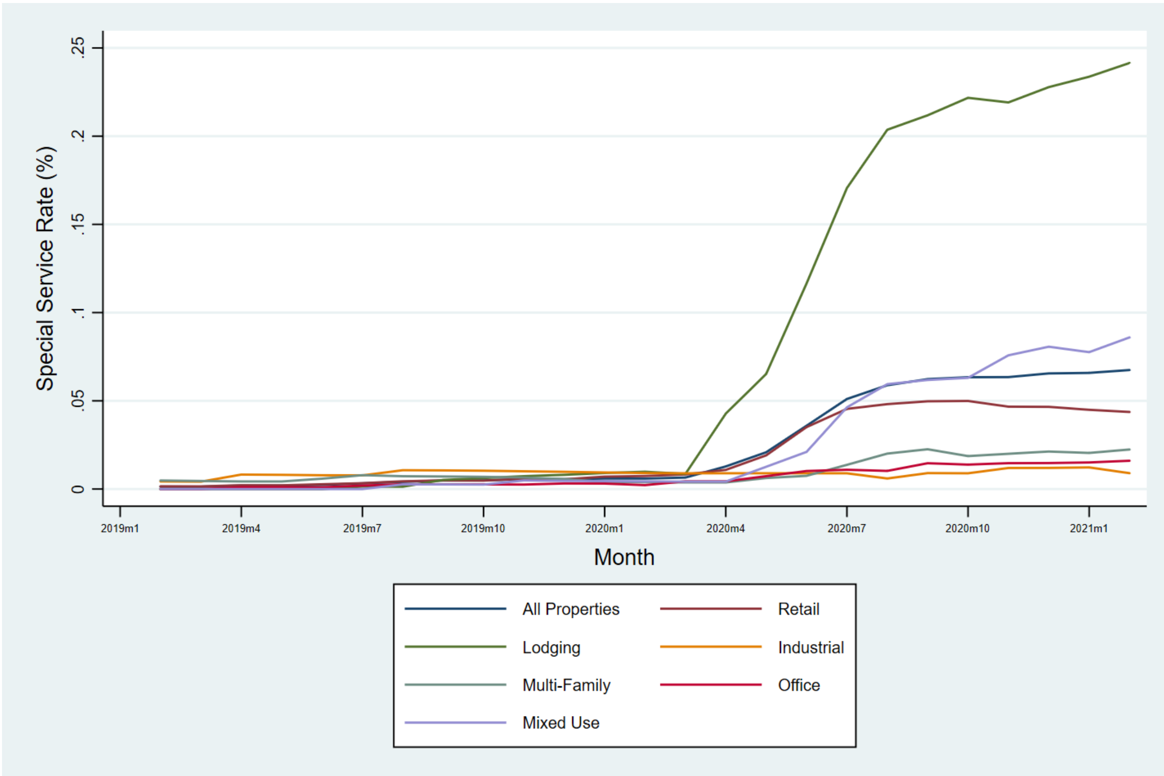
10.5 Commercial Mortgage Special Servicing

Figure 5: Commercial Mortgage Special Servicing (𝕊) Rates by Property Type



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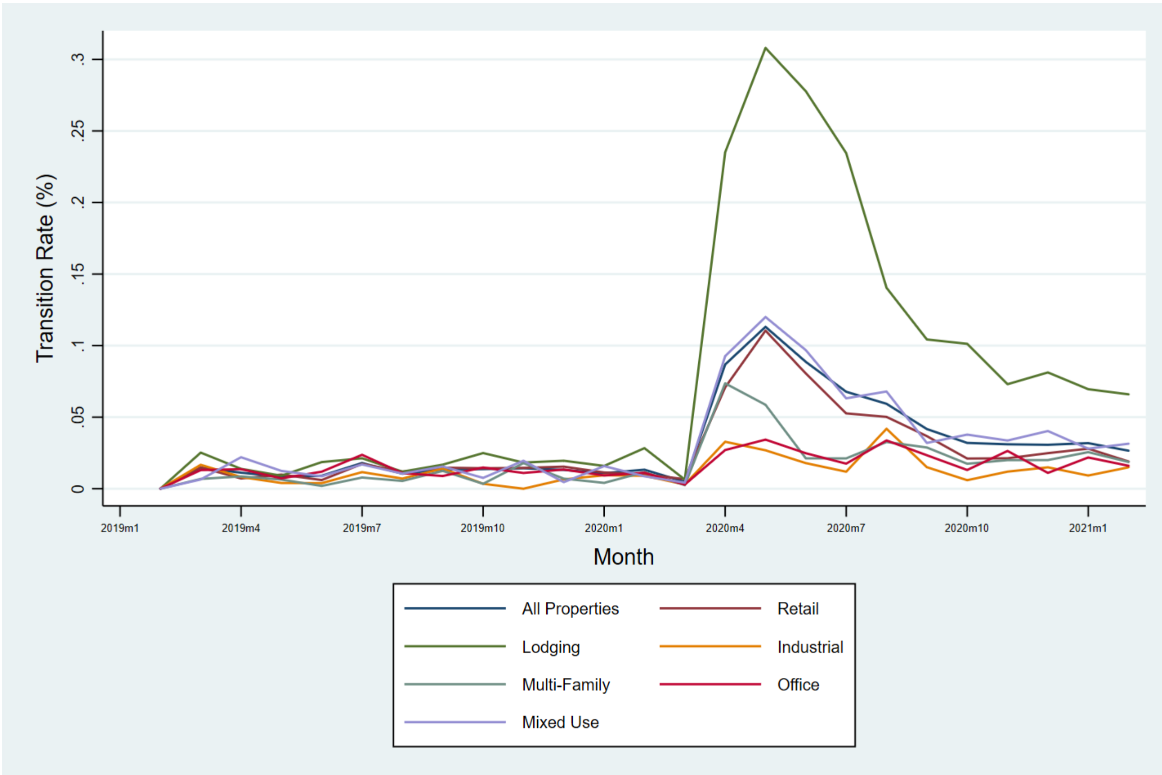
10.6 Commercial Mortgage Delinquency Transition

Figure 6: Commercial Mortgage Special Delinquency Transition ($\mathbb{T}$) Rates by Property Type



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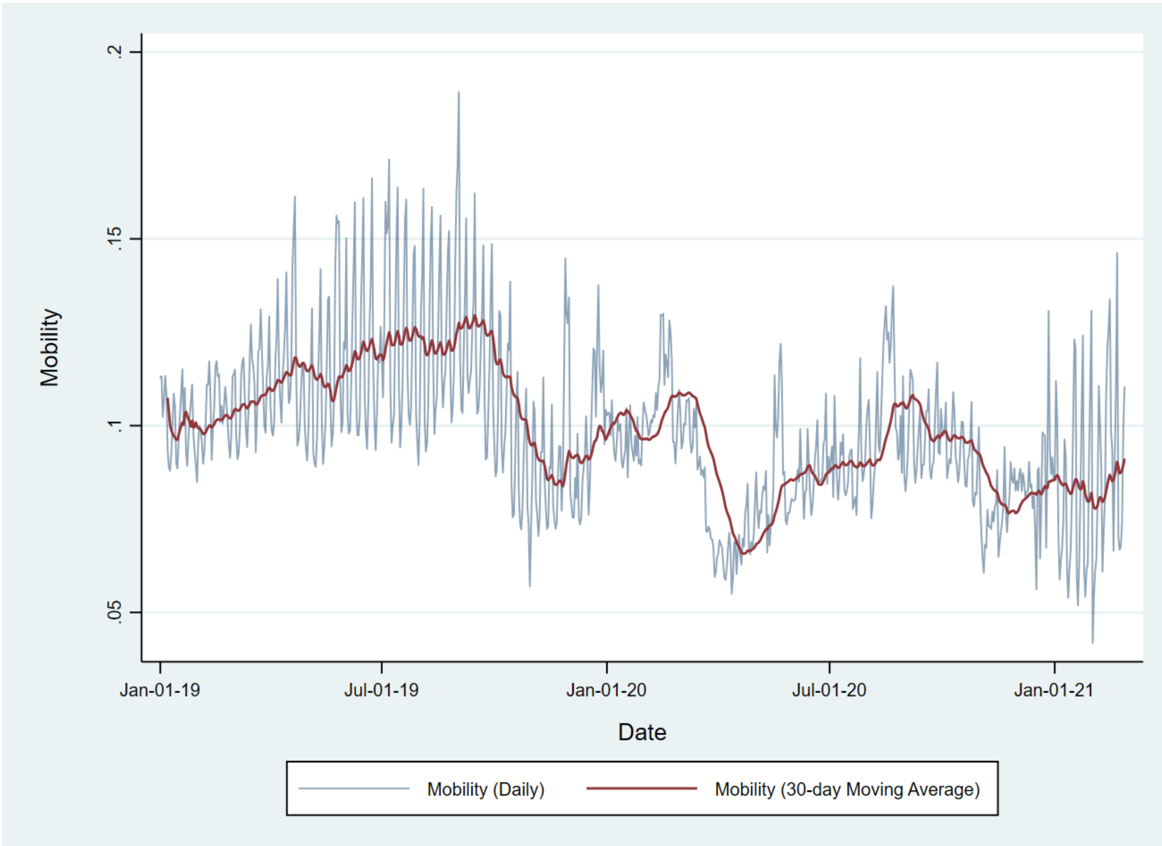
10.7 Mobility Overtime: Harris County, TX

Figure 7: Mobility Overtime (Harris County, TX)



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11 Appendix

11.1 A Note on Hyperlinks in this Paper

The entire *Contents* section is hyperlinked in **black** to the corresponding sections in the paper. Links that direct the reader to other sections of paper are given in blue. The majority of these links are connected to the references section or the tables/figures included in aggregate after the paper's reference table. Finally, links that direct to the reader to external websites are colored in purple. These are mostly for data sources and ways to quickly find online versions of papers included in the references section. The color distinction from blue links is made for the courtesy of the reader, who could be disinterested or cautious of following any external links.

11.2 Property Type Descriptions

Forthcoming.

11.3 Dictionary of Relevant Financial Terms

Retail, Office, lodging, mixed-use, multi-family, and industrial.

11.4 CMBS Security Full Sample List

Forthcoming.