Essays on Forecasting in Finance

by

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Abstract

This dissertation is composed of three essays related to forecasting in various financial markets. The first essay reviews over 60 studies published from 2008 to 2021 that investigate the causes of the mortgage crisis leading to the Great Recession. Because the mortgage crisis led to significant changes in finance, economics, law, education, and other areas, the causes and potential solutions to it have been studied extensively. Other literature reviews since 2008 that focus on mortgage crisis research have highlighted subprime mortgages defaults and determinants of mortgage defaults. This literature review contributes to the mortgage crisis research by reviewing several other areas related to the causes and resolution of the mortgage crisis, including foreclosure laws, securitization, and strategic default.

This review is particularly timely, considering the amount of upheaval in real estate and mortgage markets caused by coronavirus disease 2019 (COVID-19). Some economists are concerned that COVID-19 could trigger another mortgage crisis with significant economic spillover. Although such a crisis is difficult to forecast, this literature review provides a much-needed compilation of work spanning multiple fields that could help avert or ameliorate another crisis. Despite the various methodological approaches used and differing data sources, many studies come to similar conclusions on the effects of laws, securitization, borrower characteristics, and neighborhood characteristics on default and foreclosure.

Many of the studies on foreclosure laws find that laws designed to help prevent foreclosure (recourse versus non-recourse and judicial versus non-judicial) only extended the foreclosure timeline and did not actually prevent foreclosure. Furthermore, most of the research related to securitization of loans found that securitized loans had a higher rate of foreclosure compared to portfolio loans. Within the arena of strategic default, studies find that emotions and morality play a significant role, but education, information, and lender relationship are also important factors.

The second essay examines the forecasting ability of banks in response to changes in local housing prices. Using Freddie Mac housing prices, banking data from the Federal Deposit Insurance Corporation, and mortgage rates from RateWatch, I measure the impact of changes in housing prices on changes in mortgage rates. RateWatch provides branch level rates, which in turn allows a much finer degree of granularity regarding local mortgage rates than previous studies. Thus, by using the RateWatch data, this study contributes to both the real estate literature and the banking literature by tying mortgage rate-setting decisions to local house price movements, increasing our understanding of rate-setting decisions and the effects of centralized rate-setting. The major finding of this essay is that during the incredible housing price expansion from the late-1990s to the mid-2000s, local lenders adjusted mortgage rates faster than non-local lenders in response to changes in house prices. However, in the housing price crash following the runup, there was no difference in how local and non-local banks adjusted rates.

The final essay develops a technical analysis-based model for forecasting in the stock market. Technical analysis is widely used in the practice of managing investment portfolios, but approaches used to study technical analysis in most academic research do not mimic actual usage within the industry. This study fills a significant gap by replicating more accurately the application of technical analysis in portfolio management through the use of a unique probit model. The probit model uses variables derived from five common technical analysis indicators to forecast one month in advance. Using S&P values from 1871 to 2019, probit market-timing model outperforms the standard buy-and-hold portfolio in out-of-sample tests. Out-performance is particularly notable in periods of high volatility, while during calm, steady uptrends, the model tends to match market performance.

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List of Abbreviations

2SLS	2-stage least squares
3SLS	3-stage least squares
401(k)	an employer-sponsored defined-contribution pension account defined in subsection 401(k) of the Internal Revenue Code
ARM	Adjustable-Rate Mortgage
B&H	buy-and-hold
BB	Bollinger Bands
BLL	Brock, Lakonishok, and LeBaron
CBSA	core-based statistical area
CM	Cumby-Modest
COVID-19	coronavirus disease 2019
CRSP	Center for Research in Security Prices
EMA	exponential moving average
ETF	exchange traded fund
FDIC	Federal Deposit Insurance Corporation
FMHPI	Freddie Mac House Price Index
fMRI	functional magnetic resonance imaging
FRED	Federal Reserve Economic Data
FRM	Fixed-Rate Mortgage
HARP	Home Affordable Refinance Program
HM	Henriksson-Merton
HPI	House Price Index
HPR	holding period return
IRA	individual retirement account

IV	instrumental variable
LBB	lower Bollinger Band
LPM	linear probability model
MA	moving average
MACD	Moving Average Convergence / Divergence
MACI	moving average crossover indicator
MBB	middle Bollinger Band
NRTZ	Neely, Rapach, Tu, and Zhou
OLS	ordinary least squares
OOS	out-of-sample
REO	real estate owned
RS	Resnick and Shoesmith
RSI	Relative Strength Index
SMA	simple moving average
STO	Stochastic Oscillator
STW	Sullivan, Timmermann, and White
TA	technical analysis
UBB	upper Bollinger Band
WRDS	Wharton Research Data Services

Chapter 1

Foreclosure, Securitization, Default, and Subprime Lending: A Review of the Literature

1.1. Introduction

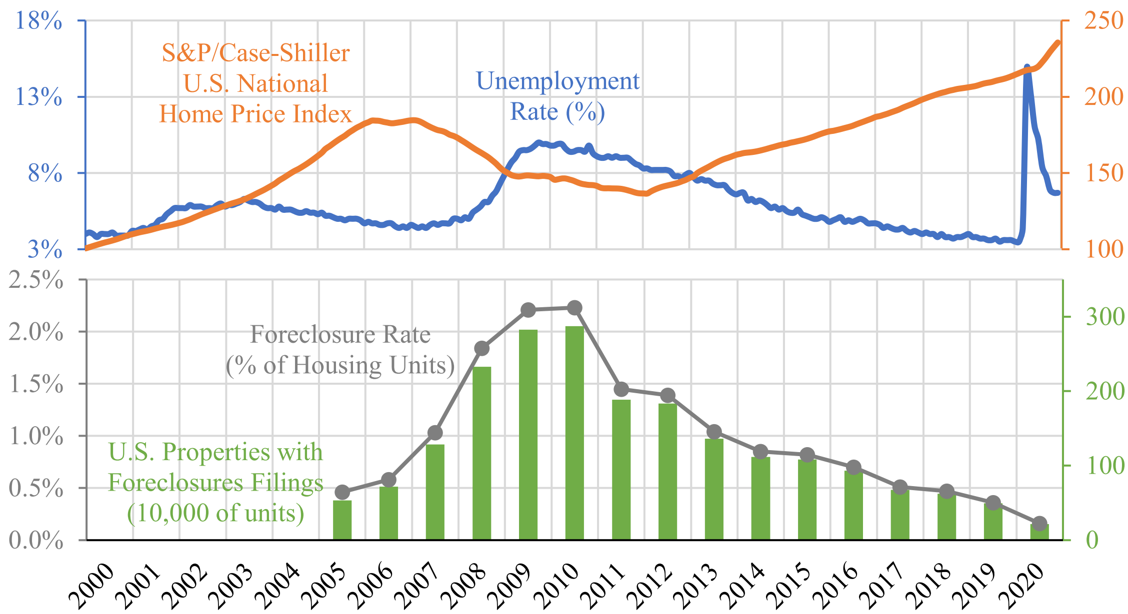
Since the Great Recession, there has been substantial interest in real estate research topics broadly defined. That is particularly true of topics dealing with mortgage default and foreclosure. Researchers from a variety of disciplines have weighed in on the subject across a spectrum of academic outlets. While other literature reviews (see Jones and Sirmans, 2015 and 2019) have highlighted research regarding specific areas related to mortgages, the need for a reference resource to identify other applicable works motivates this literature review.

Foreclosures increased dramatically from 2005 to 2010 as the housing bubble burst and unemployment rose across the country (see Figure 1.1). However, previous related literature reviews focused on subprime defaults and the determinants of residential defaults. This essay fills a necessary gap in research literature by reviewing influential works on foreclosure laws, the effects of foreclosures, and what influence securitization has on foreclosure. Additionally, this review extends the work of previous literature reviews by compiling research on subprime origination, strategic default, default in general, and other topics relevant to the mortgage crisis.

This work is particularly timely in the wake of the coronavirus disease 2019 (COVID-19). Some economists are concerned that COVID-19 could cause another mortgage crisis with significant economic spillover. The Great Recession brought about significant changes in lending practices, finance and economic theory, and borrower education, and it is critical to understand what actions were helpful and what can be done in the event of a similar crisis. Although such a crisis is difficult to forecast, this literature review provides a much-needed compilation of literature that could help avert another crisis.

Figure 1.1. Foreclosures in the United States compared to House Prices and Unemployment

S&P/Case-Shiller and Unemployment Rate data come from Federal Reserve Economic Data (FRED) online database. Data for U.S. Properties with Foreclosure Filings and Foreclosure Rate come from ATTOM Data Solutions. The top half of the figure plots the monthly U.S. unemployment rate in blue with the scale on the left against the S&P/Case-Shiller U.S. National Home Price Index in orange with the scale on the right. The bottom half of the figure plots the annual rate of foreclosures in the U.S. in gray with the scale on the left and the total number of annual foreclosure filings in the U.S. in green with the scale on the right.



In this essay, we review over 60 articles published from 2008 to 2021. In addition to summarizing the major findings in each paper, research is compared to the results of similar articles, and a chart at the end of each section details the sample, model, and variables used in each paper. These charts should help future researchers plan the development of research as they study the effects of COVID-19 on housing prices, mortgages, defaults, and foreclosures.

This essay is organized in the following manner. In the next section, we look at the literature related to Foreclosure Laws. After that, we examine What Happens During and After Foreclosure. Then, we review Securitization and Foreclosure/Modification literature. That section is followed by Subprime Origination, Strategic Default, and Default in General. Finally, we review Other Relevant Research and conclude with a short summary.

1.2. Foreclosure Laws

There has been interest in the role of state foreclosure laws. Curtis (2014) finds that states with foreclosure laws that favor lenders experience greater subprime lending activity, but that this effect is not present in the prime lending market. Ong, Neo, and Tu (2008) note the requirement that foreclosed borrowers in Singapore must pay the lender any shortfall from the foreclosure sale, contrary to most American mortgages. They use this fact to analyze loss aversion and disposition effects, finding that individual property owners display behaviors consistent with both theories. Lenders seeking to dispose of foreclosed properties do not.

Desai, Elliehausen, and Steinbuks (2013) find that default rates are higher in judicial foreclosure states, and the impact changes across risk profiles of the loan products offered. That is, the impact is largest for the riskiest category of subprime Adjustable-Rate Mortgages (ARM) and smallest for the least risky category of prime Fixed-Rate Mortgages (FRM). They also report that default rates are lower in states with larger homestead exemptions in bankruptcy.

Cordell et al. (2015) find that increased time to resolve foreclosures during the housing crisis increased costs significantly for mortgage lenders and servicers. These effects were particularly pronounced in states that require judicial foreclosure. After the onset of the housing crisis, foreclosure timelines increased by about seven months in nonjudicial foreclosure states and twenty months in judicial foreclosure states. This increased direct costs to the foreclosing party by about four percent of the outstanding loan balance in nonjudicial states and fifteen percent in judicial states. Indirect costs associated with foreclosures lingering on the market would only add to the toll, and especially so in judicial foreclosure states.

Gordon and Winkler (2015) investigate statutory right of redemption, which allows foreclosed property owners to redeem the property for some period of time after a foreclosure auction. They find that statutory redemption is relatively rare, but it can result in substantial losses to the property owner holding the property after auction. They find evidence that the auction price, which they model as the strike price in their option theoretic framework, has a significant impact on the subsequent net selling price of the house.

Mian, Sufi, and Trebbi (2015) find that borrowers in nonjudicial foreclosure states were more than twice as likely to face foreclosure as borrowers in cross-border judicial foreclosure states. They trace this difference in propensity to foreclose into the housing markets by showing that the areas where foreclosure was more likely experienced a large jump in housing supply that served to depress house prices. The reduced house prices are further tied to reduced capital expenditures on housing and reduced consumption more broadly. As the wave of foreclosures receded, foreclosure rates in judicial and nonjudicial states converged, and nonjudicial jurisdictions saw a stronger recovery in house prices.

Zhao, Wang, and Sing (2019) analyze the impact of foreclosure laws on supply of mortgage credit and default rates. They use the same border identification strategy as is seen in a number of prior works, but they allow for more realistic variation across all three components of foreclosure laws that might differ across borders: judicial foreclosure requirements, existence of statutory right of redemption periods, and non-recourse laws for mortgage loans. Accounting for potential differences across all three aspects of foreclosure laws, they find no evidence that foreclosure regimes impact supply of mortgage credit or default rates of borrowers.

Dagher and Sun (2016) find that the supply of credit is limited in states that require judicial foreclosure for loans above the conforming loan limit. Similarly, Cao and Liu (2016) find that lenders tend to make riskier loans in states where foreclosure laws favor lenders more heavily (i.e. states that allow non-judicial foreclosure) and in states with lower homestead exemptions in bankruptcy proceedings. Cao and Liu (2016) also present limited evidence that FHA loans and subprime loans are substitutes.

Bao and Ding (2016) compare house price movements in states that allow lenders to pursue borrowers for any loan balance not covered in a foreclosure sale (i.e. recourse states) versus states that cut off the lender's interest at the conclusion of the foreclosure sale (i.e. non-recourse states). They find that non-recourse states experience higher price appreciation during the bubble period, larger price declines during the bust period, and faster recovery during the recovery period. In other words, non-recourse states experience higher home price volatility.

Ghent and Kudlyak (2011) find that borrowers in states that allow lenders to pursue deficiency judgments are less likely to default for all price ranges above a $200,000 appraised value at origination. This is interpreted as evidence that at least some defaults must be strategic. Further, the authors report that lenders in recourse states are more likely to foreclose via a lender-friendly method. Chan et al. (2016) have a different take on the impact of foreclosure laws on default. They examine the link between spillover in primary mortgage foreclosures to other debt markets. Whether a borrower's primary mortgage is nonrecourse affects other home loans and credit card default rates. Nonrecourse primary loans increase mortgage default probability of primary loans by 2.6 percentage points, secondary loans by the same amount, and home equity loans by 3.2 percentage points. But credit card default is reduced by 2.4 percentage points for nonrecourse primary mortgages. On the flip side, homeowners that can delay foreclosure due to recourse are likely to have an increase in credit card default; compared to a delay of 3 months or less than, the probability of credit card default for homeowners able to live in their houses for over 9 months rent-free increases by 7.7 percentage points.

Gerardi, Lambie-Hanson, and Willen (2013) find that laws which are designed to protect borrowers from foreclosure do not prevent foreclosures, but they do delay foreclosures. Using a difference-in-difference approach to compare Massachusetts to the surrounding states around the time Massachusetts implemented a "right-to-cure" law, Gerardi et al. (2013) find that the law had no influence on mortgage modifications or on borrowers curing their mortgage defaults. While the law may have delayed imminent foreclosure, it does not appear to have prevented it, and may in fact have simply increased lenders' costs.

Table 1.1. Foreclosure Laws

Author(s) and Year	**Location**	**Year**	**Sample**	**Model**	**Variables of interest**
Ong, Neo, and Tu (2008)	Singapore	1992-2003	72,504 transactions	Multinomial logit	price volatility myopic expectation Truncated Loss
Ghent and Kudlyak (2011)	United States	1997-2008	2.9 M loans	Probit	recourse LTV deeds in lieu short sales
Desai, Elliehausen, and Steinbuks (2013)	United States	1998-2006	44 M loans	OLS	default foreclosure rate start foreclosure rate share
Gerardi, Lambie-Hanson, and Willen (2013)	United States	2000-2011	Randomly-selected 10% of 29 M loans	OLS	legal regime
Curtis (2014)	United States	2005-2006	12 M loan applications	OLS	Foreclosure law index Anti-predatory lending index Foreclosure delay
Cordell, Geng, Goodman, and Yang (2015)	United States	1998-2013	3.5 M loans	Accelerated Failure Time	Redemption States Deficiency Judgment Default Period
Gordon and Winkler (2015)	Madison County, Alabama	2004-2012	1,942 foreclosures	Hedonic Pricing	Right of Redemption timing

Author(s) and Year	Location	Year	Sample	Model	Variables of interest
Mian, Sufi, and Trebbi (2015)	United States	2006-2013	County-level Foreclosure data	Discontinuity 2SLS	Judicial foreclosure requirement Distance from state border Foreclosures per homeowner
Zebian and Dusansky (2015)	United States	2007-2008	Theoretical based on Case-Shiller Index	Recursive Equilibrium	Taxing imputed rents Deductibility of interest mortgage payments
Bao and Ding (2016)	United States	2000-2013	Quarterly data for 100 MSAs	Panel Data Regression	recourse boom burst
Cao and Liu (2016)	United States	2004-2008	HMDA data for 181 counties	Probit	Judicial foreclosure requirement Redemption Deficiency Judgment (recourse) Bankruptcy homestead exemption
Chan, Haughwout, Hayashi, and Van Der Klaauw (2016)	United States	2002-2011	396,924 Observations from 49,481 mortgages	Linear Probability	LTV mortgage balance change in HPI
Dagher and Sun (2016)	United States	2001-2006	1.3 M loan applications	Linear Probability	Judicial foreclosure requirement Redemption Deficiency Judgment (recourse)
Zhao, Wang, and Sing (2019)	United States	1999-2012	556,004 FRMs	Cox Proportional Hazard	Judicial foreclosure requirement Redemption Deficiency Judgment (recourse)

1.3. What Happens During and After Foreclosure

Chan et al. (2014) investigate what happens between default and resolution. They find that foreclosure avoidance via loan modification, refinancing, or sale of the property versus foreclosure is influenced by loan characteristics, borrower credit history and post-default behavior, neighborhood characteristics, and borrower race and ethnicity. Chan, Dastrup, and Ellen (2016) find that property owners are slow to update their estimates of home values. Across all homeowners, there is a tendency to overstate property values when property values are declining, but not during better market conditions. This phenomenon is particularly acute among property owners with little or no equity in their homes. The authors report that almost half of borrowers categorized as underwater in their sample do not perceive themselves as being underwater.

Conklin (2017) finds that borrowers who work directly (i.e., face-to-face meetings) with a mortgage broker during the loan origination process are less likely to subsequently default on the loan. This result is driven by borrowers who are likely to be less financially literate: borrowers from areas of low educational attainment, low-income borrowers, borrowers with low credit scores, and minority borrowers. The paper by Pennington-Cross (2010) focuses on what happens to subprime mortgages that are in foreclosure proceedings. While foreclosure duration is influenced by many factors, shorter durations tend to end in real estate owned (REO) status, and longer durations are predominately exited by loan payoffs. Only a small portion of subprime loans were fully or partially cured.

Donner (2017) looks at foreclosures in Stockholm, Sweden. He finds that foreclosed properties are resold shortly after a foreclosure. Furthermore, many of the buyers of foreclosed properties purchased more than one foreclosure. Both the quick resale of foreclosures and the purchase of multiple properties by a single buyer point to professional buyers purchasing significantly discounted properties with the intent to make a quick capital gains profit. Examining data from Fresno, California, Aroul and Hansz (2014) also find that foreclosed properties are sold at a discount. The discount associated with foreclosure is approximately 20%, while short sales are discounted approximately 13%. Interestingly, foreclosure actually decreases time on market while short sale increases time on market.

According to the research of Li (2016), for the three-year period prior to foreclosure, capital expenditures on REO properties is significantly less than for non-foreclosed properties. This decreased capital expenditure during the foreclosure proceedings comes through two major channels: reduced expenditure by homeowners going through foreclosure who are disincentivized to spend on home improvement and lenders who are unwilling to invest capital in their REO inventory. While capital expenditure does increase in the year after the sale, the increase is less than the decrease in spending prior to the sale.

Table 1.2. What Happens During and After Foreclosure

Author(s) and Year	**Location**	**Year**	**Sample**	**Model**	**Variables of interest**
Pennington-Cross (2010)	United States	2001-2005	5000 subprime loans	Mixed Multinomial logit	Time in foreclosure
Aroul and Hansz (2014)	Fresno, California	2006-2010	22,362 home sales	Hedonic with 2SLS and 3SLS	time foreclosure short sale
Chan, Sharygin, Been, and Haughwout (2014)	New York City	2003-2008	140,033 subprime and Alt-A securitized mortgages	discrete time proportional hazard	months since default loan characteristics borrower characteristics neighborhood characteristics borrower behaviors
Chan, Dastrup, and Ellen (2016)	United States	1996-2010	47,000 survey responses and 12,875 household waves	OLS	change in HPI lagged LTV
Li (2016)	Milwaukee	2005-2009	13,191 transactions	Tobit	average capital expenditure neighboring foreclosures house price trend owner to tenant ratio
Conklin (2017)	United States	1998-2005	394,483 mortgages	Probit	Face-to-face interview between broker and borrower
Donner (2017)	Stockholm, Sweden	2005-2014	249 foreclosed homes	Propensity score, probit	Time to resale Return prior to foreclosure Return after foreclosure

1.4. Securitization and Foreclosure/Modification

Adelino, Gerardi, and Willen (2014) find that securitized mortgages are more likely to be modified and less likely to be foreclosed. On the other hand, Kruger (2018) finds that securitization increased foreclosure rates during and after the crisis. Using hand-collected contractual terms of servicing agreements and the August 2007 freeze of private securitization, Kruger (2018) finds that servicers have incentives that favor foreclosure over modification, even though the mortgage servicers have the freedom to modify the mortgages.

The results from Agarwal et al. (2011) agree with those from Kruger (2018). Agarwal et al. (2011) find that mortgages held by banks as portfolio loans were 26 to 36% more likely to be modified than comparable mortgages that were securitized. Furthermore, they also find that modifications of mortgages owned by banks have lower default rates post-modification. Thus, mortgages that were securitized were less likely to be modified, and those that were modified were more likely to subsequently default.

Agarwal, Chang, and Yavas (2012) sheds some light as to why bank-held mortgage modifications and default rates differ from securitized mortgages. They find that banks retained a higher proportion of the higher-default-risk mortgages originated between 2004 and 2007 and sold a relatively higher proportion of the lower-default-risk loans originated during this time period into the secondary market. However, the mix shifted after 2007, when banks were no longer willing to hold as many of the higher-default-risk loans.

In examining loan modification for subprime borrowers, the results of Piskorski, Seru, and Vig (2010) are similar to those of Agarwal et al. (2011). Subprime mortgages that were held by the banks had a significantly lower foreclosure rate than comparable loans that were securitized, conditional on those mortgages being seriously delinquent. This indicates that bank-held mortgages were more likely to be modified than those that were securitized.

Table 1.3. Securitization and Foreclosure/Modification

Author(s) and Year	Location	Year	Sample	Model	Variables of interest
Piskorski, Seru, and Vig (2010)	United States	2005-2008	6,200,000 mortgages	Logit, Hazard	delinquent loan held on lender's balance sheet
Agarwal et al. (2011)	United States	2007-2009	34,000,000 mortgages	OLS	delinquent loan held on lender's balance sheet
Agarwal, Chang, and Yavas (2012)	United States	2004-2007	39,000,000 mortgages	Multinomial logit	FICO score
					borrower's income
					LTV ratio
					Conforming loan
					Jumbo loan
					low- or no-doc loan
Adelino, Gerardi, and Willen (2014)	United States	2005-2008	40,000,000 mortgages	2SLS IV with LPM & Probit	private-label securitization
					early payment default
Kruger (2018)	United States	2007-2011	1,900,000 mortgages	2SLS IV with LPM & Probit	private-label securitization

1.5. Subprime Origination

Agarwal et al. (2012) also analyze contagion effects, but they focus on negative spillover impacts related to subprime mortgage origination. They find that a higher neighborhood concentration of subprime loans does not lead to a higher probability of default for a given borrower. However, a higher concentration of alternative loan products, such as hybrid adjustable-rate mortgages or low documentation loans, does increase the probability of default for a given borrower.

Agarwal, Ambrose, and Yildirim (2015) model the expected impacts from introduction of subprime mortgages into an area where prime mortgages were previously the norm. Higher subprime default rates lead to larger numbers of foreclosures, which depress surrounding property prices. In turn, this leads to higher default probabilities for the prime mortgages in the area. Their model predictions are borne out in their empirical analysis. This default contagion from subprime borrowers to prime borrowers is also a key feature of the model developed by Ascheberg et al. (2014). They interpret the implications from their model as support for the notion that monetary policy can better address mortgage default and falling home prices, rather than fiscal policy aimed at encouraging looser mortgage credit terms.

Table 1.4. Subprime Origination

Author(s) and Year	**Location**	**Year**	**Sample**	**Model**	**Variables of interest**
Agarwal et al. (2012)	Maricopa County, Arizona	2000-2008	461,729 securitized mortgages	proportional hazard	Zip code concentration of loan types
Ascheberg et al. (2014)	United States	1987-2000	theoretical dynamic simulation	theoretical dynamic simulation	
Agarwal, Ambrose, and Yildirim (2015)	United States	2003-2008	data from 10,000 zip codes	OLS	subprime mortgage origination activity

1.6. Strategic Default

Seiler et al. (2012) analyze survey results to provide evidence on strategic versus non-strategic (or involuntary) default. They find that there are differences among three distinct types of involuntary default and between involuntary default and strategic default when it comes to the emotional response people have to their own default, how they communicate the default to others, and how people view defaults by others. They find little support for the importance of state recourse laws, bankruptcy exemptions, foreclosure laws, or right of redemption laws.

Seiler, Collins, and Fefferman (2013) model strategic default as an epidemiological event, and they find that influential members of social networks could cause a downward cascade of house prices by convincing underwater homeowners of the acceptability of strategic default. Seiler, Lane, and Harrison (2014) report results from a related experiment designed to test herding behavior regarding strategic default. They find that subjects exhibited herding behavior in terms of willingness to default, particularly when the peer information provided to subjects included a default decision of a perceived expert. The herding behavior was ameliorated when the subject expressed a moral objection to strategic default before the experiment. Seiler (2015a) explores the results from a similar experiment and finds that subject behavior fits the definition of herding better than it fits the definition of an information cascade. This categorization is inferred from the provision of an informationally equivalent private signal after the experiment has begun that results in a change in likelihood of strategic default. The study also shows that subjects respond more to advice than to observed actions of others in making the decision to strategically default.

Using an online sample, Seiler (2015b) finds that there is a significant perception gap among the public about the likelihood that a lender will pursue a deficiency judgment. In reality, lenders rarely pursue such judgements for a variety of reasons. However, survey respondents assigned a very high probability to this possible outcome of a decision to strategically default. This widely held misperception, combined with the common view of strategic default as immoral, is keeping strategic default rates lower than they otherwise would be. Thus, Seiler (2015b) recommends a continued policy of informational opacity regarding actual deficiency judgment cases if the policy goal is to minimize strategic default.

Seiler (2017b) tests whether a liquidated damages clause in a mortgage changes the prevailing view among the public that mortgage default is immoral. Results support the conclusion that, when liquidated damages are present, the public does not view mortgage default as negatively, except in the case of strategic default. The moral objection to strategic default is strong enough to overcome the ameliorating effects of the liquidated damages clause. Results are similar regardless of the type of debt considered: mortgage, car loan, credit card debt, or cell phone contract.

Seiler (2014) conducts an experiment in which participants choose whether to strategically default on their mortgage. The results show that borrowers are less likely to strategically default when they have a long-term relationship with their lender, and borrowers are more likely to strategically default when they perceive that their lender has misbehaved. The propensity to strategically default is greatly reduced when the lender signals their willingness to cooperate with the borrower via a loan modification.

Seiler and Walden (2014) use functional magnetic resonance imaging (fMRI) technology to shed light on borrower thought processes related to strategic default. They find that borrowers are less likely to default when social norms paint defaulting in a negative light and that borrowers will seek retribution (via default) when a lender refuses a loan modification. Seiler and Walden (2015) use the same fMRI technology to provide evidence against borrowers falling victim to the sunk cost fallacy in their consideration of strategic default. However, borrowers do appear to suffer from cognitive dissonance resulting from the moral case against default versus the financial case for default. Seiler and Walden (2016) use fMRI technology once again to differentiate between the thought processes of borrowers considering strategic default when they are provided information about peer defaults versus when they are provided information from a perceived real estate expert. They find that peer defaults are viewed as reducing the stigma associated with strategic default, but that borrowers do not seek to replicate peer behavior regarding default. Conversely, borrowers are much more likely to strategically default if a perceived real estate expert advocates for that course of action. Seiler (2017a) takes the brain function explanation a step further by identifying a genetic marker associated with a higher likelihood of a borrower choosing to strategically default.

Collins, Harrison, and Seiler (2015) present a game theoretic model of borrowers' decisions to strategically default. They show that it is rarely in lender's interest to allow a loan modification. They further show that the size of the negative equity position, expected growth rate of house prices, and perceived probability that the lender will pursue a deficiency judgment are the most important considerations for the borrower in weighing the decision to strategically default. Seiler (2016) attempts to add to this theoretical underpinning of the strategic default decision by hypothesizing a theoretical cumulative distribution function based on existing empirical and experimental data.

Guiso, Sapienza, and Zingales (2013) use survey data to estimate the willingness of borrowers to strategically default. They find willingness increases with the level of negative equity faced by the borrower. They also find that the willingness to strategically default is affected by non-monetary factors (e.g., morality) and exposure to other strategic defaulters. Finally, they also report evidence of a desire for retribution as a factor in the strategic default decision-making of some borrowers.

Bradley, Cutts, and Liu (2015) put together a very detailed dataset from CoreLogic and Equifax that allows for very precise definition of strategic default. They find that the incidence of strategic default is likely not as high as reported in other studies, although they point out that the incidence is certainly high enough to warrant concern. They find that strategic default is associated with high loan-to-value ratios, high credit scores, and the presence of foreclosures and strategic defaults near the subject property.

Bhutta, Dokko, and Shan (2017) exploit a uniquely rich loan dataset to analyze the threshold at which underwater borrowers will strategically default. They find strong evidence that the classical option-theoretic model of mortgage default is inadequate to explain their results. The median borrower in their sample would not strategically default until they were in a negative equity position of 74% of home value. They point to the need to understand the behavioral factors obviously at play in this decision.

Gerardi et al. (2018) use new supplemental data added to the Panel Study of Income Dynamics to construct detailed budgets aimed at delineating between ability and willingness to continue making mortgage payments. They find that almost 40% of defaulting borrowers could continue making their mortgage payment without cutting current consumption. They also find that job loss has an effect equivalent to a 35% loss in equity position with regard to increasing a borrower's propensity to default. Interestingly, they find that 96% of borrowers with low equity who have the ability to pay continue to do so, and 80% of borrowers who must cut consumption to subsistence levels also remain current on mortgage payments.

Ahlawat (2019) analyzes Fannie Mae loan performance data to differentiate between strategic and non-strategic default (ruthless and non-ruthless default, in the author's terminology). He further shows that mortgages where non-strategic default has occurred are subsequently much more likely to become current again.

Zebian and Dusansky (2015) develop a model of housing and mortgage default choices. Using 2007 ownership and default data, they calibrate their model and test how changes in the tax code affects default rate. They find that by removing mortgage interest deductions and taxing imputed rents, the foreclosure rate was reduced by 33.4%. However, the homeownership rate was reduced by almost the same amount, 33.1%.

Mayer et al. (2014), using Countrywide loans, find that strategic defaults of mortgages increased in response to an announcement by Countrywide to settle a lawsuit by the U.S. state attorneys general. To be eligible for a modification program, borrowers had to be in default. Thus, Countrywide's borrowers were incentivized to default on their mortgages. The study by Mayer et al. (2014) find that the greatest increase in estimated default rates belongs to borrowers who were estimated to be least likely to default. The research by Zhu and Pace (2015) examine the effect if closure delay on default. They find that the value of default for the borrower increases as the length of the time from the first missed payment to the foreclosure date increases. Thus, as the expected length of the foreclosure period increases, so does the probability of default.

Table 1.5. Strategic Default

Author(s) and Year	**Location**	**Year**	**Sample**	**Model**	**Variables of interest**
Seiler et al. (2012)	United States	2010	878 survey responses	Logit	Loan Knowledge Emotional Drivers Bankruptcy Laws Real Estate Laws Demographic Characteristics
Guiso, Sapienza, and Zingales (2013)	United States	2008-2010	1,000 survey responses	Probit	size of home equity shortfall pecuniary costs nonpecuniary costs
Seiler, Collins, and Fefferman (2013)	United States	theoretical simulation	theoretical simulation	social network agent-based	Individual Susceptibility to Normative Influence Individual Connectivity
Mayer et al. (2014)	United States	2005-2009	750,000 mortgages	Probit	loan serviced by Countrywide time frame dummy
Seiler (2014)	United States		Experimentally collected data from 880 participants	"between subjects" experimental design, Logit	Bank type
Seiler and Walden (2014)	U.S. city		fMRIs from 20 homeowners during a survey	*T*-test	Mean Strategic Default Willingness
Seiler, Lane, and Harrison (2014)	U.S. city	2011	1365 survey responses	*T*-test	Mimetic Herding scores
Bradley, Cutts, and Liu (2015)	United States	2008-2011	135,025 observations	Logit	local foreclosure rate local strategic default rate
Collins, Harrison, and Seiler (2015)	United States	theoretical simulation	theoretical simulation	Game-tree to find Nash-equilibrium	Negative equity position Months left on mortgage Annual property growth rate Probability of recourse
Seiler (2015a)	United States	2013	1,539 survey responses	Logit	response to action response to advice response to action and advice response to attorney advice
Seiler (2015b)	United States		1,845 survey responses	Logit	Micro perspective variables Macro perspective variables
Seiler and Walden (2015)	U.S. city		fMRIs from 20 homeowners during a survey	Logit	down payment size equity loan balance
Zebian and Dusansky (2015)	United States	theoretical simulation	Theoretically calibrated for 2007	recursive equilibrium	US housing tax regime
Zhu and Pace (2015)	United States	2004-2012	200,000 loans	Logit	redemption recourse foreclosure delay

Author(s) and Year	Location	Year	Sample	Model	Variables of interest
Seiler (2016)	United States	Early 2010s	Multiple surveys	Graphical	Negative equity position Home prices Morality
Seiler and Walden (2016)	U.S. city		fMRIs from 20 homeowners during a survey	ANOVA	willingness to default influencer type
Bhutta, Dokko, and Shan (2017)	AZ, CA, FL, NV	2006-2009	128,248 non-prime loans	discrete-time hazard	cumulative LTV
Seiler (2017a)	United States		Cheek swabs from 17 participants	Lab test	COMT gene
Seiler (2017b)	United States	2014	1,938 survey responses	"between subjects" experimental design	Liquidated Damages
Gerardi et al. (2018)	United States	2009, 2011, 2013	7,404 households	2SLS IV with OLS & Probit	LTV Residual income House price appreciation Job loss disability employment shock
Ahlawat (2019)	United States	2000-2015	34,800,000 mortgages	Option-theoretic	CLTV length of delinquency

1.7. Default in General

Archer and Smith (2013) find evidence that euphoria, or investor sentiment, played a role in the high default rates observed during the bursting of the housing bubble. They present evidence that both borrowing and lending decisions during the housing bubble were based, at least in part, on the erroneous assumption that recent past price appreciation was a reliable indicator of future housing market performance.

Calem and Sarama Jr. (2017) investigate borrower behavior when there are two mortgages collateralized by the same property. They seek to explain why borrowers sometimes default on only one debt obligation. They find that stable property values and an income shock perceived as moderate or temporary will lead to default on only one mortgage, followed by cure as soon as practicable. Borrowers facing a more severe or permanent income shock will sell the property is they have positive equity or default if they do not. Expectations surrounding future house price appreciation can play an important role when the borrower is near the negative equity cutoff.

Boehm and Schlottmann (2017) develop a joint probability model of the likelihood that a borrower develops a mortgage payment problem, the likelihood they take action to address the problem given that a problem exists, and the likelihood that a borrower recovers from the problem if they fail to act. One can then calculate the probability that a borrower will not recover from a mortgage payment problem once one is encountered. Boehm and Schlottmann (2020) on the second stage identified in their prior work: taking action to address a mortgage payment problem. They find that education level, age, and previous foreclosures affect the likelihood that a lender agrees to a borrower's modification request. Education level and how early the borrower seeks help are significant in determining success of any modification that is granted.

Do, Rösch, and Scheule (2020) point out that some defaulted loans result in zero losses to lenders because those loans are paid in full, or cured. They present evidence that cured loans are more associated with default due to some type of liquidity shock, such as a temporary income interruption. Loans that do not cure, and hence result in a loss to the lender, are more associated with negative borrower equity in the property.

Heinen et al. (2021) investigate whether there is spatial dependence between mortgage defaults. They find evidence to support spatial dependence, but they cannot rule out the possibility that the spatial dependence could be serving as a proxy for unobserved factors.

Using loan-level data of 30-year fixed-rate mortgages from Freddie Mac, Zhu et al. (2015) find a 10 to 11% reduction in the monthly default hazard when mortgage payments were reduced by 10% through refinancing under the Home Affordable Refinance Program (HARP). Thus, loans that received larger payment reductions had significantly lower default rates.

In a thorough analysis of literature related to residential mortgage defaults, Jones and Sirmans (2015) review an extensive number of articles on the determinants of mortgage terminations from the 1990s through 2014.[1] The review by Jones and Sirmans (2015) builds on the work of Quercia and Stegman (1992) by analyzing more recent mortgage default literature, to include research surrounding the Great Recession. Jones and Sirmans (2015) find that the greatest predictor of individual borrower default decisions are loan characteristics. Among borrower attributes, the FICO score rates as the strongest predictor of default.

Similar to their 2015 work, Jones and Sirmans (2019) review a fairly exhaustive set of articles with a focus on subprime mortgage defaults, specifically research related to subprime mortgage defaults during the Great Recession.[2] Jones and Sirmans (2019) divide the literature into five separate areas including predatory lending and associated laws, the slump in the appreciation of home prices, subprime mortgage securitization, credit risk and underwriting standards models, and alternative mortgage products. Jones and Sirmans (2019) identify the major findings for each of the five areas. They also show how both the supply-side and demand-side contributed to the 2007 housing collapse, and suggest a need for increased oversight of the subprime market.

Table 1.6. Default in General

Author(s) and Year	**Location**	**Year**	**Sample**	**Model**	**Variables of interest**
Quercia and Stegman (1992)	United States	1962-1992	40 research studies	Lit Review	Residential default
Archer and Smith (2013)	Florida	2001-2008	965,000 loans	Logit	pre-origination local appreciation LTV Put option FICO Debt-to-income ratio
Jones and Sirmans (2015)	United States	1962-2013	81 research studies	Lit Review	Residential default

[1] The list of articles surveyed is almost exclusively different from the list surveyed in this review, by design.

[2] Again, by design, the list of articles surveyed is almost exclusively different from the list surveyed in this review.

Author(s) and Year	Location	Year	Sample	Model	Variables of interest
Zhu et al. (2015)	United States	2009-2013	64,810 HARP refinances; 2.06 M loan-month records	Cox relative risk hazard function	Payment Reduction Current LTV Post-HARP-FICO House price appreciation
Boehm and Schlottmann (2017)	United States	2009, 2011, 2013	6,338 observations	Logit	mortgage characteristics household financial characteristics household demographic characteristics state mortgage laws market/neighborhood characteristics
Calem and Sarama Jr. (2017)	United States	2005-2013	13,363 matched loan pairs	Logit	borrower equity borrower liquidity borrower credit score unemployment rate HELOC
Jones and Sirmans (2019)	United States	2000-2017	66 research studies	Lit Review	Subprime default
Boehm and Schlottmann (2020)	United States	2009, 2011, 2013	1,417 homeowners	Logit	Mortgage Characteristics Household Financial Characteristics Household Demographic Characteristics Local Economic Conditions
Do, Rösch, and Scheule (2020)	United States	2005-2015	509,408 defaulted loans	Heckman selection	borrower liquidity constraints Home Equity
Heinen et al. (2021)	Los Angeles	2000-2011	31,962 loans; 239,486 quarter-loan observations	Multinomial Logit, copula	geographic distance

1.8. Other Relevant Research

Campbell and Cocco (2015) develop a new model of mortgage default that is a bit more expansive than previous iterations of such models.

Bond et al. (2017) find that mortgage priority conventions reduce refinancing of small loans and loans near the conforming loan limit. Thus, second mortgages are valuable to lenders as a way to reduce the likelihood of borrower refinancing.

Fishback et al. (2011) present an analysis of the impacts from the Depression-era Home Owners' Loan Corporation as a guide to understanding potential impacts from similarly-designed entities intended to address the recent housing crisis.

Ghent (2011) analyzes a sample of Depression-era loan data to determine the propensity of lenders to engage in loan modification. Finding a very low propensity of 1930s lenders to engage in loan modification is used as evidence that securitization will not contribute to lower levels of loan renegotiation.

Favara and Giannetti (2017) document that lenders are less willing to foreclose in areas where the lender holds a high concentration of outstanding loans. The lenders' concern is that foreclosure will lead to price declines, which in turn lead to more foreclosures. Thus, the lender internalizes the spillover effect that would have happened had the foreclosure taken place. Lenders with high concentrations of loans in a particular area are more willing to negotiate modifications, and those geographic areas experience fewer foreclosures and smaller price declines.

1.9. Summary

While it remains to be seen how COVID-19 will affect house prices and mortgage foreclosures, the looming end of the current government-mandated moratorium on foreclosures is a potential source of concern. Some economists worry that another mortgage crisis is developing. This essay highlights important research on the mortgage crisis that led to the Great Recession, and lenders and governments should be aware of this research so that useful steps can be taken to reduce the possibility of another crisis happening.

In the area of foreclosure law, many of the studies find that laws designed to help prevent foreclosure (recourse versus non-recourse and judicial versus non-judicial) only extended the foreclosure timeline, and did not actually prevent foreclosure. Related research has shown that extending foreclosure timeframes can actually make a crisis worse, so federal and state government should enact just and equitable policies that limit the length of foreclosure proceedings. Furthermore, most of the research related to securitization of loans found that securitized loans had a higher rate of foreclosure compared to portfolio loans. Perhaps lenders need to hold a larger portion of their mortgages in their own portfolios. The research also highlights the need for better financial education for borrows, more accurate information on borrower options, and that the borrow-lender relationship is important. While it may be difficult to make borrower and lender relations better, lenders and local government can take positive action to education and inform borrowers.

Chapter 2

Mortgage Rate-Setting: Local vs. Multimarket Banks

2.1. Introduction

"All real estate is local" is a common adage heard in discussions of real estate whenever real estate salespeople or investors from more than one geographic area congregate. Reichert (1990), among others, provides empirical results to support this adage. It is telling that one does not hear the same refrain among real estate lenders when geographically diverse groups of lenders meet. Much real estate lending is not local, as multimarket lenders set mortgage rates across wider geographical areas than local market lenders. The purpose of this study is to examine whether the decision to pull rate-setting responsibilities up the organizational hierarchy affects bank responsiveness to local market developments.

In this study, we examine how banks adjust mortgage rates in response to changes in local housing prices in the pre-and post-peak timeframes of the mid-2000s mortgage crisis. Specifically, we study whether the response of local community banks is different than that of non-local, regional, or national banks in adjusting mortgage rates to changes in housing prices both before and after the local market peaks. Also, we investigate whether the nature of the core-based statistical area (CBSA) in which a bank operates impacts the responsiveness of local and non-local banks to housing market changes.

The study contributes to the real estate literature by tying mortgage rate-setting decisions to local house price movements. We provide a better understanding of the role that housing prices play in local lending decisions (i.e., mortgage rate-setting). There are two main channels through which housing prices could influence local lending decisions: (1) lender reactions to short-term stimuli (e.g., a change in local housing prices over the past month) and (2) lender reactions to longer-term stimuli (e.g., differences in lender behavior across housing markets with different historical levels of price variation). More broadly, the study also adds to the literature surrounding the subprime mortgage lending crisis that ultimately led to the Great Recession.

The study also contributes to the banking literature by increasing our understanding of rate-setting decisions and the effects of centralized rate-setting. We explore the difference in mortgage rate changes between local market and multimarket lenders, which also allows us to comment on the practice of higher-level rate-setting at larger banks. Based on research that indicates bidirectional causality between housing prices and mortgage rates, banks should adjust mortgage rates in response to changes in housing prices. The financial condition of a community bank, in particular, depends on the economic prosperity of its operating area, thus local banks have a vested interest in setting interest rates that manage the bank's own risk while supporting local economic growth. Conversely, large regional and national banks are less dependent on the economic tides of any given local market and could thus potentially afford to be less conscientious in their rate-setting choices in a particular operational area if a policy of uniform rate-setting across multiple trade areas makes more sense for that bank. On the other hand, larger banks presumably have more resources and more analytical capacity to devote to understanding local real estate price dynamics, while community bankers should know their markets better than an analyst sitting in the corporate office two states away. In short, the nature of the relationship between local house price movements and mortgage rate-setting is an empirical issue.

The remainder of the study proceeds as follows: Section 2 provides a review of the most relevant real estate, mortgage, and banking literature, Section 3 details the data and methodology utilized, Section 4 presents the findings, and Section 5 contains some concluding remarks.

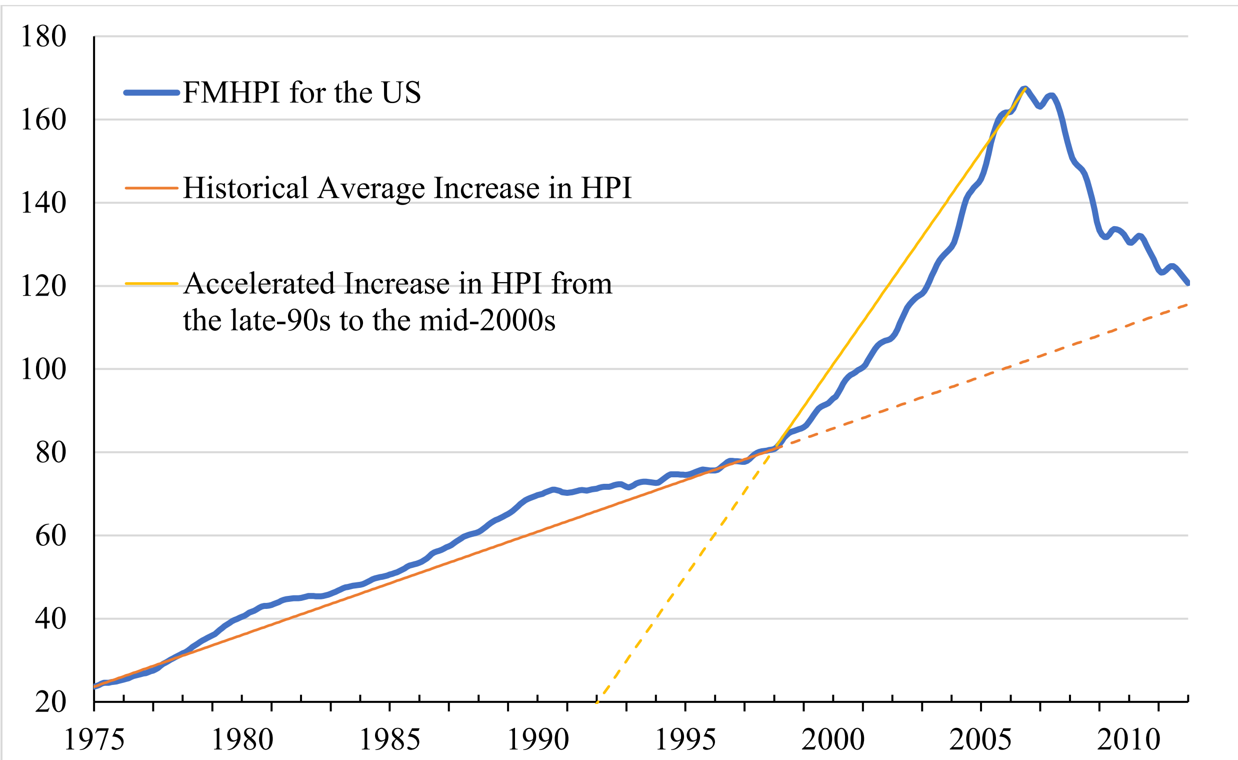
2.2. Literature Review

Housing prices for the United States peaked in July 2007, according to the Freddie Mac House Price Index (HPI) that tracks national house price data. This peak was preceded by a rapid appreciation in house prices that was dramatically above the historical average, as seen in Figure 2.1. However, there were drastic differences across states and cities in both the speed of housing price increases and the timing of the housing price peak. Adelino, Schoar, and Severino (2016) argue that the significant increase in housing prices that began in the late 1990s led many home buyers and mortgage lenders to form expectations of continued, similar increases in home prices in the early 2000s. Based at least in part on this expectation of continued above-average price appreciation, many borrowers took on larger mortgages than they could afford and many lenders accommodated those loans (see Griffin and Maturana (2016a), Griffin and Maturana (2016b), and Dickerson (2009)).

Borrowers and lenders are both rightfully concerned about interest rates, although the nature of their concern differs substantially. The primary concern of borrowers is to find the lowest rate possible, which results in either a lower payment for a given loan amount or a larger loan amount (i.e., the ability to purchase a more expensive property) if payment is allowed to fluctuate. Lenders are concerned about interest rates in terms of both profit and risk. Lenders want to generate a profit on the differential between the interest rates charged on loans and their cost of funds, but they also want to charge an appropriate interest rate to compensate for the riskiness of the loan type being considered. As housing prices continued to appreciate more and more quickly, borrowers' perception of the risk-reward tradeoff inherent in homeownership shifted, as did the perception of lenders regarding risk levels of residential mortgage lending. When house prices began declining, oftentimes quite suddenly in a given market, perceptions of borrowers and lenders shifted once again. The change in perspective for borrowers regarding the risks of owning one's own home led to a wave of strategic and forced defaults, which impacted lenders profits as it became clear that the interest rates lenders had charged were not sufficient to compensate for the levels of default being observed in many markets nationwide.

Figure 2.1. Freddie Mac House Price Index for the United States

Data from Freddie Mac



There is a long line of literature investigating the relationship between interest rates and house prices. Examples include Kau and Keenan (1980), Schwab (1982), Titman (1982), Harris (1989), de Greef and de Haas (2000), Sutton (2002), Cho and Ma (2006), Shiller (2007), McQuinn and O'Reilly (2008), Kim and Bhattacharya (2009), Hott and Jokipii (2012), Shi, Jou, and Tripe (2014), Tse, Rodgers, and Niklewski (2014), Bhutta and Keys (2016), Kishor and Marfatia (2017), and Sutton, Mihaljek, and Subelyte (2017). This list is not exhaustive by any means, but it gives a sense of the broad and sustained interest in the topic. The vast majority of this line of literature seeks to understand how either nominal or real interest rates, or some derivative thereof, impacts housing prices. The current study differs, in that we seek to uncover how regional housing prices might impact mortgage interest rates offered in that region.

There has also been a fair amount of research into the link between local housing markets and lenders. Guirguis, Giannikos, and Anderson (2005) explore the prediction of housing prices as it pertains to asset allocation, which includes mortgage rate-setting. Loutskina and Strahan (2009) highlight the weakened link between bank financial condition and the supply of mortgage loans, particularly illiquid loans, brought on by increased secondary mortgage market activity. Öhman and Yazdanfar (2017) investigate the impact of the volume of bank lending on housing prices. James et. al (2020) find that the performance of local banks is less sensitive to local housing prices than is the performance of non-local banks (or diversified banks, in their terminology).

Interest-rate setting has been a topic of frequent study, in works such as Banerjee, Bystrov, and Mizen (2013). Of particular interest to this study is research on the influence housing prices have on mortgage rates. As has already been noted, a large body of literature exists that points to the effect interest rates have on housing prices. However, there is also research which indicates housing prices affect mortgage loan rates. Kim and Bhattacharya (2009) find that mortgage rate Granger cause housing prices, but also that housing prices Granger cause mortgage rates. These results stand in contrast to an earlier study by McGibany and Nourzad (2004), which finds no causality in either direction. However, the different results could conceivably be explained by the difference in market conditions prevailing during the time periods from which the data are drawn.

Several additional studies lend support to the findings of Kim and Bhattacharya (2009). In their study using data from Hong Kong, Gerlach and Peng (2005) find that prices influence lending, but the influence does not flow in the opposite direction. Using data from 17 countries, Goodhart and Hofmann (2008) find no causality from prices to interest rates in the full sample from 1973 to 2006; however, in the 1985-2006 subsample, Goodhart and Hofmann (2008) do find that prices have a causal effect on interest rates. Oikarinen (2009), Anundsen and Jansen (2013), and Öhman and Yasdanfar (2017) find bi-directional causality in prices and lending in Finland, Norway, and Sweden, respectively. Basten and Koch (2015) find similar results in Switzerland using housing supply and demand. The most recent paper by Wilhelmsson (2020) confirms the dual-causality between housing prices and interest rates.

The research on the direction of causality is important to this paper because we exploit the housing price causality on mortgage rates. This is similar to research by Chakraborty, Goldstein, and MacKinlay (2018), which shows how changes in housing prices lead to changes in bank lending practices—from commercial lending to mortgage lending as housing prices increase. Additionally, following the findings by Igan et al. (2011) that interest rates in the United States lag house prices, we use both contemporary and lagged housing prices as explanatory variables in our model.

The major contribution of this study lies in its examination of the ability of small, local banks to set mortgage rates based on expected changes in local housing prices compared to the ability of larger, national banks to set mortgage rates. The investigation of this topic adds to an already substantial rate-setting literature, but it also touches on bank organizational structure. This line of literature has also drawn significant interest over the years, and it analyzes issues surrounding which banks remain community banks and which banks grow into larger entities, among other topics. While a full review of either the rate-setting literature or the bank organization literature is beyond the scope of the current study, there are several entries in these lines of literature worth noting. Bikker and Haaf (2002) provide an excellent starting point for the nature of competition and concentration in the banking industry. Kahn et al (2003) explore the role of small banks, noting that "community banks should continue to play an important role in the banking system by … specializing in relationship-based services." Emmons, Gilbert, and Yeager (2004) study risk reduction in community banks and argue that, in order to survive, community banks will have to grow in size while still providing services based on relationships. Hein, Koch, and Macdonald (2005) build on the previous two works and ultimately agree that relationship-based services will have to remain an important component of community banking.

More closely related to the current study is the work of Dlugosz et. al (2021). They provide evidence that banks forecast short-term interest rates and incorporate those short-term predictions into their rate-setting for loan and deposit rates. We build on this finding by asking whether greater geographic dispersion in the data that drives such forecasts impacts the appropriateness of the rates that come out of the models.

2.3. Data and Methodology

2.3.1. Data

The data for our study comes from four main sources: Freddie Mac, RateWatch, the Federal Deposit Insurance Corporation (FDIC), and the United States Census Bureau. Other potential data sources include Zillow, the Federal Financial Institutions Examination Council (FFIEC), the U.S. Department of Housing and Urban Development (HUD), the Federal Reserve (Fed), and others. Details and definitions of the variables are found in Table 2.1.

Freddie Mac provides monthly HPI data beginning in 1975 for 382 core-based statistical areas (CBSA) as defined by the United States Office of Management and Budget. RateWatch loan rate data include the interest rates of loans charged by banks over 3000 banks and other lending institutions in 365 CBSAs and 50 states and districts (there are no data for Hawaii, but there are data for the District of Columbia). Our RateWatch data begin in January 2001 and ends in February 2020. The FDIC provides quarterly financial data for banks beginning in the final quarter of 1992. The Census Bureau estimates county populations annually, and the estimates are available back to 1970.

Table 2.1. Variable Definitions

Variables of Interest	
$\%\Delta Rate_{i,t,k,c}$	The percentage change in the quarterly interest rate charged by the local branch of lending institution *i* in quarter *t* from quarter *t*-1 for a specific mortgage product *k* in a particular CBSA *c*.
$Non\text{-}Local_{i,t}$	A dummy variable that uses 1 to indicate that lending institution *i* is a large regional or national lender during quarter *t* and 0 to indicate that bank *i* is a local community lender during quarter *t*. The value of this variable is fixed at the beginning of our timeframe and does not change.
$\%\Delta HPI_{t,c}$	The percentage change in the Freddie Mac HPI in quarter *t* from quarter *t*-1 for a particular CBSA *c*. *Lagging %Δ HPI* is for quarter *t*-1, or the percentage change from the two quarter ago to the last quarter, relative to the quarter of *Rate*. *Current %Δ HPI* is for month *t*, or the percentage change from the last quarter to this quarter, relative to the quarter of *Rate*.
Bank controls	
$\text{Ln}(\#\ of\ Employees)_{i,t}$	The natural log of the number of employees of lending institution *i* in quarter *t*. For non-local institutions, this is based on the number of employees in the entire corporation, not just the local branch.
$\text{Ln}(Assets)_{i,t}$	The natural log of the assets of lending institution *i* in quarter *t*. For non-local institutions, this is based on the assets of the entire corporation, not just the local branch.

CBSA controls	
Ln(*Population*)$_{t,c}$	The natural log of the population of CBSA *c* in quarter *t*.
%Δ *Population*	The percentage change in the population of CBSA *c* in quarter *t* from quarter *t*-1.
High Cost CBSA$_{t,c}$	A dummy variable that uses 1 to indicate that the HPI level in CBSA *c* is above the median in quarter *t*, and 0 otherwise.
Mortgage Product subsamples	
ARM$_{t,k}$	Mortgage products can be divided between Adjustable-Rate Mortgages (ARM) with adjustment periods of 1, 3, 5, and 7 years and Fixed-Rate Mortgages (FRM) with terms of 10, 15, 20, and 30 years. *ARM* is a dummy variable that uses 1 to indicate that mortgage product *k* is an ARM in quarter *t*, and 0 to indicate that mortgage product *k* is a FRM.
CBSA subsamples	
Volatile CBSA$_{t,c}$	A dummy variable that uses 1 to indicate that the volatility of the HPI in CBSA *c* is above the median in quarter *t*, and 0 otherwise.
High Pop CBSA$_{t,c}$	A dummy variable that uses 1 to indicate that the population of CBSA *c* is above the median in quarter *t*, and 0 otherwise.

The data from FDIC on bank assets and employees is reported quarterly. Therefore, model estimations are accomplished using quarters as the appropriate unit of time. Population estimates from the Census Bureau are reported annually as of the 3rd quarter of each sample year. To get quarterly estimates of population, we interpolate the values for each quarter between those Census Bureau estimates. Quarterly mortgage rate data are the average quarterly rate for each specific mortgage type (1-, 3-, 5-, or 7-year Adjustable-Rate Mortgage (ARM) or 10-, 15-, 20-, or 30-year Fixed Rate Mortgage (FRM)) at each local bank branch or non-local bank branch within a given CBSA.

Geographic control is accomplished using the smallest area possible given the limitations of the available data. The Freddie Mac HPI data are reported based on core-based statistical areas, which is the current umbrella term for both micropolitan and metropolitan areas. RateWatch data include both the county and the CBSA where lending institutions are located. Thus, combining the

HPI data with the RateWatch data is relatively seamless. The Census Bureau, however, reports population estimates at the county level in non-census years. In order to generate CBSA population estimates for those between-census sample years, we use the Census Bureau county-level estimates and combine all counties that are contained within a CBSA. Many CBSAs consist of a single county, so no adjustment is needed. However, there are several CBSAs that are a combination of many counties, sometimes crossing state lines in major urban areas.

We focus our study on the timeframe around the local CBSA house price peak. The data used in our models include the five years before and three years after the local CBSA peak in house prices, if the data are available. The earliest CBSA to peak was Detroit-Warren-Dearborn, MI in June of 2005, and the latest CBSA to peak was College Station-Bryan ,TX in September of 2008. We limit the sample period to three years after the peak because the house price trough for several CBSAs was less than four years after the peak. Accordingly, the data used in our regressions begin in the 4th quarter of 2002 (the first data available for the Detroit-Warren-Dearborn, MI CBSA) and ends in the 3rd quarter of 2011 (three years after the peak in College Station-Bryan, TX).

Table 2.2 displays summary statistics for several variables. Of particular interest is the difference between the mortgage rates charged by local banks and non-local banks. In every sample year, for every mortgage product considered, local banks charge a rate that is different than their non-local competitors. This begs the question of whether there is a difference in rate changes by local lenders compared to non-local lenders in response to changes in housing prices.

Table 2.2. Summary Statistics

Panel A: Mortgage Rates by Loan Type		
	FRM	ARM
Local	5.867	5.801
Non-Local	5.816	5.551

Panel B: Mortgage Rates by Loan Type and Terms		
	FRM	ARM
	10-Year	1-Year
Local	5.698	5.226
Non-Local	5.566	5.070
	15-Year	3-Year
Local	5.701	5.882
Non-Local	5.606	5.526
	20-Year	5-Year
Local	6.104	6.064
Non-Local	6.014	5.772
	30-Year	7-Year
Local	6.039	5.894
Non-Local	6.045	5.929

Panel C: Mortgage Rates by Loan Type and Year of Origination		
	FRM	ARM
	2002	
Local	5.918	5.528
Non-Local	5.794	5.022
	2003	
Local	5.674	5.052
Non-Local	5.563	4.665
	2004	
Local	5.725	5.200
Non-Local	5.658	4.893
	2005	
Local	5.916	5.774
Non-Local	5.850	5.616
	2006	
Local	6.413	6.568
Non-Local	6.381	6.427
	2007	
Local	6.337	6.588
Non-Local	6.326	6.484
	2008	
Local	5.981	5.983
Non-Local	5.989	6.192
	2009	
Local	5.257	5.575
Non-Local	5.105	5.323
	2010	
Local	4.930	5.212
Non-Local	4.632	4.595
	2011	
Local	4.875	4.900
Non-Local	4.483	4.475

Table 2.2. Summary Statistics (continued)

Panel D: Housing Price Index Averages by Year		
	Level	**%Δ**
2002	110.47	0.58%
2003	118.35	0.53%
2004	128.27	0.67%
2005	139.56	0.63%
2006	146.19	0.13%
2007	146.03	-0.19%
2008	137.49	-0.64%
2009	129.24	-0.16%
2010	126.88	-0.32%

2011	122.70	-0.19%

Note: The percent change in the housing price index is computed as the average monthly percentage change for each sample year.

Panel E: Sample Banks by Type and Year		
	Local	**Non-Local**
2002	7,142	8,905
2003	6,683	8,277
2004	7,301	8,914
2005	7,967	9,342
2006	7,838	8,857
2007	7,561	8,337
2008	7,099	7,923
2009	6,710	7,433
2010	6,485	7,182
2011	6,762	7,177

2.3.2. Methodology

As a starting point for answering the questions posed above, we look at the change in interest rates charged by lending institutions around the time the housing market peaked in each CBSA. In Table 2.3, we display the mean month-over-month change in the rate charged by banks for their mortgage products one and two months prior to the housing price peak in the local area. Ex ante, there is reason to believe that lenders in housing markets with greater volatility in house prices might face a harder task in incorporating house price information into their rate-setting. Therefore, we divide the mean month-over-month rate changes between CBSAs with relatively more volatile housing prices and relatively less volatile housing prices. In almost every case, the difference in the rate change between local lenders and non-local lenders appears to be substantial.

We formally evaluate the difference between mortgage rate changes made by local banks and non-local banks in response to changes in local housing prices with the following model:

$$\%\Delta Rate_{i,t,k,c} = \%\Delta HPI_{t,c} + \%\Delta HPI_{t\text{-}1,c} + Non\_Local_{i,t} + B\_X_{i,t} + C\_X_{t,c} + Mort\_I_{t,k}, \quad (1)$$

where $\%\Delta$ *Rate*, $\%\Delta$ *HPI*, and *Non_Local* are as described in Table 2.1; *B_X* and *C_X* are the vectors of banking control variables and CBSA control variables, respectively, in Table 2.1; and *Mort_I* is the indicator variable for mortgage type, either *Mort_Type* or *ARM*, as detailed in

Table 2.1. The results of ordinary least squares (OLS) regressions with robust standard errors based on this model are displayed in Tables 2.4 through 2.9.

Table 2.3. Percentage Change in Mortgage Rate Offered Before Local Market Downturn

Two Months Before Downturn				
	Low Volatility CBSA		High Volatility CBSA	
	FRM	ARM	FRM	ARM
	10-Year	1-Year	10-Year	1-Year
Local	4.46%	1.19%	2.14%	1.77%
Non-Local	-0.25%	2.79%	1.12%	4.20%
	15-Year	3-Year	15-Year	3-Year
Local	3.57%	2.55%	2.26%	2.01%
Non-Local	3.26%	2.63%	2.29%	2.37%
	20-Year	5-Year	20-Year	5-Year
Local	4.48%	2.89%	-0.04%	1.73%
Non-Local	2.63%	2.48%	2.43%	2.20%
	30-Year	7-Year	30-Year	7-Year
Local	3.35%	3.48%†	2.38%	3.67%
Non-Local	3.17%	2.11%	2.31%	1.27%

Table 2.3. Percentage Change in Mortgage Rate Offered Before Local Market Downturn (continued)

One Month Before Downturn								
	Low Volatility CBSA				High Volatility CBSA			
	FRM		ARM		FRM		ARM	
	10-Year		1-Year		10-Year		1-Year	
Local	2.15%		2.46%		1.30%		1.54%	
Non-Local	2.12%		1.73%		1.10%		2.20%	
	15-Year		3-Year		15-Year		3-Year	
Local	1.08%		0.78%		1.43%		1.06%	
Non-Local	1.35%		2.28%		1.44%		2.21%	
	20-Year		5-Year		20-Year		5-Year	
Local	0.33%		0.96%		1.79%		1.45%	
Non-Local	0.73%		1.82%		0.60%		1.53%	
	30-Year		7-Year		30-Year		7-Year	
Local	1.57%		1.16%‡		1.40%		0.91%	
Non-Local	1.38%		2.05%		1.29%		1.68%	

Note: High volatility in the local price index is defined as volatility greater than the median housing price index volatility over the sample period.
†, & ‡: Limited observations for these results; 15 and 19 observations, respectively.

2.4. Results

In Table 2.3, there is clearly a difference in how local lenders and non-local lenders change the mortgage rates they are charging borrowers. We begin to explore what may be driving those differences in Table 2.4. In Model 1 of Table 2.4, the change in housing prices for both the current and previous quarters have a statistically significant influence on changes in mortgage rates. This is unsurprising and confirms similar findings from previous studies on the topic. However, our primary variable of interest, *Non-local*, is statistically significant. The coefficient of *Non-local* indicates that large regional and national banks adjusted their mortgage rates approximately 2% less than their local counterparts. In Model 2 of Table 2.4, we include control variable for lenders and CBSAs. With control variables included, the coefficient of *Non-local* is only marginally significant, and the difference in rate changes by local versus non-local lenders dropped by more than one-third.

Models 3 and 4 of Table 2.4 replicate Models 1 and 2, respectively, but add the *ARM* indicator variable to control for possible differences in rate setting across mortgage types. The coefficients of *Non-local* in Models 3 and 4, as well as the other coefficients that were included in Models 1 and 2, are very similar to the coefficients for those same variables in Models 1 and 2. However, the coefficient for the *ARM* dichotomous variable is statistically significant in both models. This coefficient indicates that initial rates on ARM loans are adjusted upward by nearly 5½% more than FRM loans on average. Across all four models included in Exhibit 5, the variable of interest, *Non-local*, is significant. That is, large regional and national banks adjust their mortgage interest rates significantly less than do community banks serving the same communities.

We now turn our attention to what may be driving that difference in rate-setting across lender types. Based on the significant difference in rate-setting for ARMs and FRMs that shows up in Models 3 and 4 of Table 2.4, we divide our sample into two subsamples of only ARMs and only FRMs, and we rerun the same regressions reported above. In Table 2.5, Models 5 and 6 repeat the Models 1 and 2 regressions, respectively, shown in Table 2.4, but Models 5 and 6 use the only-ARM subsample. Models 7 and 8 repeat the Table 2.4, Models 1 and 2 regressions, respectively, but they use the only-FRM subsample. The variable of interest, *Non-local*, is significant in Models 5 and 7. However, when the control variables related to bank size and CBSA size are included in Models 6 and 8, *Non-local* loses significance. There is clearly some difference in rate setting between local and non-local lenders, but the difference cannot be explained solely by focusing on loan type.

Table 2.4. Mortgage Rate Changes as a Function of Housing Prices Changes and Lender Geographic Focus

	Model 1	Model 2	Model 3	Model 4
Non-Local Bank	-0.0218***	-0.0138*	-0.0228***	-0.0150*
	(0.0054)	(0.0080)	(0.0054)	(0.0080)
%ΔHPI	0.0321***	0.0320***	0.0322***	0.0321***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Lag %ΔHPI	-0.0096***	-0.0095***	-0.0097***	-0.0096***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Ln (# of Emp)		-0.0425***		-0.0420***
		(0.0037)		(0.0037)
Ln (Assets)		0.0427***		0.0423***
		(0.0040)		(0.0040)
Ln (Population)		0.0014		0.0010
		(0.0018)		(0.0018)
%Δ in Population		-5.2180***		-5.2189***
		(0.7217)		(0.7192)
ARM dummy			0.0542***	0.0532***
			(0.0053)	(0.0053)
Constant	0.0083*	-0.3521***	-0.0158***	-0.3673***
	(0.0043)	(0.0419)	(0.0046)	(0.0418)
Observations	104,195	104,195	104,195	104,195
R-squared	0.0121	0.0139	0.0131	0.0149

Robust standard errors in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
All variables are as defined in Table 2.1.

Both Table 2.4 and Table 2.5 indicate that the difference across local and non-local lenders between quarter over quarter changes in interest rates of both loan types is significant. However, in the models reported in Exhibits 5 and 6, the coefficients on *Non-local* are only marginally significant in the presence of control variables. This would seem to indicate that, on average and across the full sample period, local lenders and non-local lenders adjust mortgage rates in response to changes in housing prices in a very similar fashion. However, possible drivers of this difference remain elusive and of interest. In an attempt to uncover the source of this difference, we draw on the difference in borrower and lender risk perceptions before a local peak in housing prices versus after a local peak in housing prices, as discussed above. In short, market conditions changed substantially around the local market peaks for each of our geographic areas, and market participants reacted accordingly.

Table 2.5. Mortgage Rate Changes as a Function of Housing Prices and Lender Geographic Focus by Mortgage Type

	Model 5 ARMs	Model 6 ARMs	Model 7 FRMs	Model 8 FRMs
Non-Local Bank	-0.0295***	-0.0149	-0.0168***	-0.0142
	(0.0089)	(0.0130)	(0.0065)	(0.0098)
%ΔHPI	0.0204***	0.0203***	0.0422***	0.0421***
	(0.0015)	(0.0015)	(0.0011)	(0.0011)
Lag %ΔHPI	-0.0052***	-0.0052***	-0.0137***	-0.0135***
	(0.0016)	(0.0016)	(0.0012)	(0.0012)
Ln (# of Emp)		-0.0540***		-0.0320***
		(0.0060)		(0.0044)
Ln (Assets)		0.0528***		0.0333***
		(0.0065)		(0.0049)
Ln (Population)		0.0012		0.0009
		(0.0030)		(0.0022)
%Δ in Population		-5.6994***		-4.5324***
		(1.0756)		(0.9557)
Constant	0.0488***	-0.3837***	-0.0248***	-0.3066***
	(0.0071)	(0.0678)	(0.0052)	(0.0511)
Observations	47,571	47,571	56,624	56,624
R-squared	0.0043	0.0066	0.0252	0.0265

Robust standard errors in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
All variables are as defined in Table 2.1.

The obvious extension related to the current study is whether local lenders reacted differently than did non-local lenders. In order to address this question, we subset the data according to when each local market housing market peaked. In other words, we identify each local market peak and then analyze local lender versus non-local lender behavior regarding rate setting in the run-up to each local market peak and, separately, in the aftermath of each local market crash. Stated another way, borrower and lender behavior changed when their local markets went from a period of rapidly rising house prices to a period of often dramatically declining house prices, so we divide our sample into pre- and post-peak timeframes. The results of the pre-peak regressions are displayed in Table 2.6, and the post-peak result in Table 2.7.

In all regressions using the pre-peak subsample, *Non-local* is statistically significant. Model 9 of Table 2.6 utilizes the full pre-peak subsample with no distinction as to loan type. Models 10 and 11 of Table 2.6 analyze ARMs and FRMs, respectively. When we split the pre-peak data into ARM and FRM subsamples, the coefficient on *Non-local* has a greater magnitude for ARM loans than for FRM loans. Model 12 of Table 2.6 again uses the full pre-peak subsample, but adds in the *ARM* indicator variable. The coefficients returned in Model 12 are very similar to those found in Model 9, but the change to ARM loan rates is positive and significantly greater than the change to FRM loan rates.

The results in Table 2.7 using data from the post-peak subsample stand in stark contrast to the pre-peak results reported in Table 2.6. Models 13 through 16 of Table 2.7 repeat the regressions reported in Models 9 through 12, but this time using the post-peak data: Model 13 uses the full post-peak subsample with no distinction regarding loan type, Model 14 uses the ARM subset of the post-peak subsample, Model 15 uses the FRM subset of the post-peak subsample, and Model 16 uses the full post-peak subsample with the *ARM* indicator variable included. *Non-local* is never statistically significant. However, the *ARM* indicator variable in Model 16 is positive and statistically significant, as it was in Model 12.

Table 2.6. Mortgage Rates Changes Before the Local CBSA Peak

	Model 9 All Mortgages	Model 10 ARMs	Model 11 FRMs	Model 12 All Mortgages
Non-Local Bank	-0.0419*** (0.0107)	-0.0493*** (0.0173)	-0.0367*** (0.0130)	-0.0424*** (0.0107)
%ΔHPI	0.0326*** (0.0014)	0.0291*** (0.0023)	0.0357*** (0.0017)	0.0327*** (0.0014)
Lag %ΔHPI	-0.0190*** (0.0014)	-0.0167*** (0.0024)	-0.0210*** (0.0017)	-0.0190*** (0.0014)
Ln (# of Emp)	-0.0498*** (0.0049)	-0.0612*** (0.0079)	-0.0389*** (0.0059)	-0.0494*** (0.0049)
Ln (Assets)	0.0506*** (0.0052)	0.0601*** (0.0084)	0.0413*** (0.0064)	0.0503*** (0.0052)
Ln (Population)	-0.0174*** (0.0025)	-0.0179*** (0.0041)	-0.0173*** (0.0030)	-0.0175*** (0.0025)
%Δ in Population	-2.1786** (0.9740)	-3.5571*** (1.3591)	-0.7708 (1.3590)	-2.2159** (0.9710)
ARM dummy				0.0230*** (0.0069)
Constant	-0.1243** (0.0538)	-0.1572* (0.0871)	-0.0802 (0.0654)	-0.1300** (0.0537)
Observations	66,366	30,496	35,870	66,366
R-squared	0.0091	0.0075	0.0119	0.0093

Robust standard errors in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
All variables are as defined in Table 2.1.

The results displayed in Table 2.6 and Table 2.7 are particularly interesting. Table 2.6 results indicate that non-local lenders change the interest rates charged on mortgage loans less than do local lenders in the time period leading up to the local market peak. This can be interpreted as evidence that local lenders had a better sense of how dangerous the local lending market had become, so local lenders increased mortgage rates more in order to compensate for this additional perceived risk. Stated alternatively, non-local lenders increased the interest rates on mortgages more slowly than their local competitors, encouraging additional mortgage lending at a time when mortgage lending was becoming substantially riskier. This can also be interpreted as an argument in favor of a local rate-setting policy even for larger banks that might otherwise be able to implement a statewide or multi-state interest rate policy.

Table 2.7. Mortgage Rates Changes After the Local CBSA Peak

	Model 13 All Mortgages	Model 14 ARMs	Model 15 FRMs	Model 16 All Mortgages
Non-Local Bank	0.0034 (0.0118)	0.0141 (0.0190)	-0.0061 (0.0146)	0.0017 (0.0117)
%ΔHPI	0.0296*** (0.0014)	0.0110*** (0.0023)	0.0454*** (0.0017)	0.0297*** (0.0014)
Lag %ΔHPI	-0.0012 (0.0014)	0.0054** (0.0023)	-0.0076*** (0.0017)	-0.0014 (0.0014)
Ln (# of Emp)	-0.0473*** (0.0057)	-0.0561*** (0.0096)	-0.0396*** (0.0067)	-0.0476*** (0.0057)
Ln (Assets)	0.0508*** (0.0064)	0.0585*** (0.0104)	0.0436*** (0.0077)	0.0511*** (0.0064)
Ln (Population)	0.0393*** (0.0028)	0.0325*** (0.0047)	0.0430*** (0.0034)	0.0382*** (0.0028)
%Δ in Population	-10.6716*** (1.2415)	-11.9585*** (2.1248)	-9.0874*** (1.4734)	-10.3226*** (1.2406)
ARM dummy				0.1015*** (0.0082)
Constant	-0.9783*** (0.0685)	-0.9098*** (0.1108)	-1.0006*** (0.0840)	-1.0127*** (0.0682)
Observations	37,133	16,718	20,415	37,133
R-squared	0.0210	0.0095	0.0432	0.0253

Robust standard errors in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
All variables are as defined in Table 2.1.

Subsetting the sample by certain CBSA characteristics allows for some additional insight into which geographic areas drive the observed differences between local and non-local lenders with regard to rate-setting policy. Table 2.8 shows regression results using subsamples of the data based on the median CBSA population, and Table 2.9 shows regressions results using subsamples of the data based on the median CBSA HPI volatility.

The results based on CBSA population subsamples are similar to the pre-peak and post-peak results from Models 12 and 16 with two main differences. The first difference is that the *ARM* indicator variable is insignificant in Model 17, meaning that there was no significant difference in the change in mortgage rates between ARMs and FRMs in high population areas before the peak. The second difference is that the significance level of *Non-local* drops in Model 19. This indicates that the difference between local lenders and non-local lenders in terms of changing mortgage rates is smaller in low population areas than in high population areas before the peak. More generally, and perhaps not surprisingly, given the results in Exhibits 7 and 8, the results are concentrated in the pre-peak timeframe.

In Table 2.9, *Non-local* is insignificant in Models 22 and 24, which both utilize post-peak data. Given the results reported in Table 2.6 and Table 2.7, this is not surprising. However, *Non-local* is also insignificant in Model 21, which uses pre-peak data from CBSAs with relatively higher price volatility. It is likely that due to highly volatile housing prices, both community banks and large regional and national banks struggled to adjust mortgage interest rates appropriately to changes in housing prices. Model 23 is the only model in Table 2.9 with a significant coefficient for *Non-local*. This means that non-local lenders increased their mortgage interest rates less than their local lending colleagues during the subprime mortgage lending craze.

Table 2.8. Mortgage Rates Changes based on CBSA Population

	Model 17	Model 18	Model 19	Model 20
Timeframe	Before	After	Before	After
CBSA Population	High	High	Low	Low
Non-Local Bank	-0.0492***	-0.0011	-0.0333**	0.0155
	(0.0162)	(0.0173)	(0.0141)	(0.0162)
%ΔHPI	0.0208***	0.0348***	0.0446***	0.0221***
	(0.0019)	(0.0019)	(0.0021)	(0.0020)
Lag %ΔHPI	-0.0100***	-0.0002	-0.0332***	-0.0040*
	(0.0019)	(0.0019)	(0.0022)	(0.0021)
Ln (# of Emp)	-0.0440***	-0.0711***	-0.0585***	-0.0146
	(0.0068)	(0.0076)	(0.0069)	(0.0089)
Ln (Assets)	0.0510***	0.0785***	0.0522***	0.0121
	(0.0073)	(0.0084)	(0.0075)	(0.0099)
Ln (Population)	0.0101**	0.0161**	0.0189***	0.0320***
	(0.0050)	(0.0066)	(0.0065)	(0.0080)
%Δ in Population	-6.0098***	-8.0340***	9.5749***	-10.9693***
	(0.9975)	(2.2034)	(2.0029)	(1.5004)
ARM dummy	0.0024	0.0971***	0.0365***	0.1027***
	(0.0101)	(0.0115)	(0.0095)	(0.0117)
Constant	-0.5765***	-0.9097***	-0.5616***	-0.6070***
	(0.0959)	(0.1187)	(0.1006)	(0.1305)
Observations	32,013	18,454	34,353	18,679
R-squared	0.0063	0.0344	0.0162	0.0132

Robust standard errors in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
All variables are as defined in Table 2.1.

Table 2.9. Mortgage Rates Changes based on CBSA HPI Volatility

	Model 21	Model 22	Model 23	Model 24
Timeframe	Before	After	Before	After
CBSA HPI Volatility	High	High	Low	Low
Non-Local Bank	-0.0211	-0.0044	-0.0702***	0.0038
	(0.0142)	(0.0166)	(0.0162)	(0.0165)
%ΔHPI	0.0195***	0.0282***	0.0627***	0.0384***
	(0.0017)	(0.0017)	(0.0026)	(0.0025)
Lag %ΔHPI	-0.0139***	-0.0056***	-0.0274***	0.0146***
	(0.0017)	(0.0017)	(0.0031)	(0.0025)
Ln (# of Emp)	-0.0550***	-0.0357***	-0.0465***	-0.0599***
	(0.0069)	(0.0082)	(0.0069)	(0.0080)
Ln (Assets)	0.0587***	0.0434***	0.0429***	0.0591***
	(0.0074)	(0.0090)	(0.0074)	(0.0091)
Ln (Population)	-0.0222***	0.0425***	-0.0016	0.0339***
	(0.0031)	(0.0037)	(0.0043)	(0.0044)
%Δ in Population	0.0569	-6.9517***	-3.9587***	-12.3591***
	(2.3839)	(1.9114)	(0.9867)	(1.6319)
ARM dummy	0.0199**	0.1079***	0.0216**	0.0970***
	(0.0093)	(0.0115)	(0.0103)	(0.0116)
Constant	-0.1581**	-1.0290***	-0.2522***	-0.9878***
	(0.0737)	(0.0938)	(0.0816)	(0.0997)
Observations	34,873	19,028	31,493	18,105
R-squared	0.0066	0.0277	0.0186	0.0297

Robust standard errors in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
All variables are as defined in Table 2.1.

2.5. Conclusion

Using branch-level mortgage rate data from RateWatch, combined with bank data from FDIC, population data from the Census Bureau, and housing price data from Freddie Mac, I find that local mortgage lenders adjusted mortgage rates more quickly than their multi-market counterparts in response to changes in home prices during the home price run-up from the early

2000s to the mid-2000s. However, after a local housing market peaked, there was no difference in rate adjusting behavior between local lenders and larger regional or national lenders. This pre-peak difference is particularly strong in metropolitan areas with higher populations and metropolitan areas with less volatile house prices.

These results provide support for the idea that local lenders may have some rate-setting advantage during periods of housing price growth supported by stable economic circumstances. In fact, there is some evidence that local lenders increased their mortgage rates more rapidly than non-local lenders as local housing prices neared their peak. This is interpreted as a sign that local lenders were better attuned to the risks posed by their local lending markets. However, any local advantage seems to disappear during times of high economic uncertainty and rapid house price decline. It could simply be the case that the magnitude of the government response to the housing crisis and subsequent financial crisis introduced incentives that made rate setting more uniform across lender types.

A possible fertile area of future research could investigate what led local lenders to change rates more rapidly that non-local lenders, as well as the reasons those differences in rate setting behavior disappeared post-peak. Large regional and national lenders should be aware of the possible increased risk exposure they face related to non-local rate-setting policies. This sample period covers an extreme event, to be certain, but that would seem to be exactly the time a financial institution would least like to incur increased risk exposure that could be relatively easily addressed ex-ante. Finally, this difference in rate-setting behavior should at least be something that regulators are able to consider in determining whether new regulatory guidance against regional rate-setting might be useful.

Chapter 3

Forecasting the S&P with Technical Analysis

3.1. Introduction

One of the earliest techniques used to forecast market movement is technical analysis (TA)—using historical movement of past prices and volume to forecast future price movement. This study is motivated by the fact that TA continues to be used extensively in the practice of portfolio management and market analysis, yet remains an under-researched area in financial academic research. Furthermore, most TA research evaluates a few simple rules of TA, without taking a more wholistic approach to TA as it is applied in the industry. Since the dawn of research on TA, researchers have evaluated the performance of TA market-timing methods based on simple dummy rules. For example, in their seminal work, Brock, Lakonishok, and LeBaron (1992) (hereafter BLL) use two rules—moving averages (MA) and trading ranges. Under the MA rule, if a short MA crosses above (below) a long MA, a buy (sell) signal is generated. While signals such as these are a part of TA, to evaluate the performance of TA on straightforward on/off functions to trigger a market-timing decision misses out on a majority of TA's capabilities.

This paper takes a drastically different approach to assessing the capabilities of TA. Rather than apply specific TA rules, we develop a TA-based probit model that generates a forecast for timing the market. Instead of evaluating several TA rules to determine buy or sell, the investor using our model simply sets a probability threshold, X. When the forecasted probability exceeds (is below) the X threshold, a sell (buy) signal is generated.

By applying TA in this manner, we replicate more accurately the actual use of TA in the industry. When TA is employed in the practice of wealth management, most technical analysts use multiple indicators together to make buy and sell decision. Furthermore, analysts are not only concerned about whether a certain level has been breached, but also whether indicators are increasing or decrease—and how quickly they are doing so—to determine the likelihood of an asset increasing or decreasing in price. Thus, it is reasonable to apply a probit model to TA.

We fill a significant research gap by using not just a simplistic on/off function of the indicators, but also the level of the indicators, the change in the level of the indicators, and the velocity of that change. Furthermore, our use of a probit model is also unique. Because TA is based on probabilities—identifying high probability entry and exit points—the use of a probit model mimics more closely the decisions of technical analysts than previous research.

The model we develop follows the design used by Resnick and Shoesmith (2002) (hereafter RS) based on the work of Estrella and Mishkin (1998). Our model is based solely on the price action of an asset, specifically the S&P 500® index, using the open, high, low, and closing levels of the index to generate TA indicators and inform market-timing decisions. The aim of this paper is to identify whether common TA indicators consistently provides accurate, reliable out-of-sample (OOS) stock market forecasts for the mean-variance investor. The model may also be applied to individual stocks and other asset classes.

Like RS, we do not attempt to predict the market return. Rather, our model provides investors the opportunity to move their assets from a stock portfolio investment into cash (or a safer asset) when the probability of a down month in the market reaches an established threshold. We find that an investor using our probit model to time the market by switching out of a stock index fund (cash) into cash (index fund) before a forecasted down (up) month in the market could have realized a compound annual return of 12.11% versus 9.19% from an index only buy-and-hold strategy from 1881 to 2020. We employ several robustness tests to verify our results.

The rest of this paper proceeds as follows. Section 3.2 provides a literature review. In Section 3.3, we explain our data sources, and our how are variables were created. Section 3.4 details the methodology of the probit model. Section 3.5 highlights the performance of the model. We test model robustness in Section 3.6 and in Section 3.7 we conclude with a discussion and final thoughts.

3.2. Literature Review

Research into forecasting market returns has a long history. In 1920, Charles Dow wrote in *Scientific Stock Speculation*, "that, nobody can hope to buy at the bottom or to sell at the top; or to be right all the time or to avoid losses," (Dow, 1920). A century later, research has allowed investors to buy closer to the bottom, sell closer to the top, and be right more often, but market-timers still have losses despite their best efforts; Dow's statement is still accurate.

Research into market outperformance using TA has blossomed in the century since Charles Dow wrote his book. Early works include Cowles and Jones (1937) which investigated timing based on market periodicity and Ketchum (1947) which evaluated various market timing plans for investment management. In the 1960's and 70's, both Fama and Blume (1966) and Jensen and Benington (1970) researched mechanical, TA-based trading rules proposed by Alexander (1961 and 1964) and Levy (1967a and 1967b), respectively, while Zakon and Pennypacker (1968) analyzed the advance/decline line technical indicator.

Toward the end of the last century, the theoretical model of Brown and Jennings (1989) shows that TA has value to investors. In their 1992 work, BLL find that simple TA rules have strong predictive power. Even though Sullivan, Timmermann, and White (1999) (hereafter STW) find that the market outperformance of TA in BLL was insignificant in OOS tests, later research supports the findings of BLL.

Significant growth in the amount of academic literature on TA has taken place since the turn of the century (see Leigh, Paz, and Purvis, 2002; Mizrach and Weerts, 2009; Menkhoff, 2010; Shynkevich, 2012; Lin, 2018; among others). An instrumental paper published at the beginning of the century by Lo, Mamaysky, and Wang (2000) noted, "One of the greatest gulfs between academic finance and industry practice is the separation that exists between technical analysts and their academic critics." More recently, the findings of Han, Yang, and Zhou (2013) and Neely, Rapach, Tu, and Zhou (2014) (hereafter NRTZ) agree with those of BLL that simple TA rules have strong predictive power. Two other papers on TA analyze the results of published TA research articles or recommendations and find that TA is valuable for investors, out-performing buy-and-hold and fundamental analysis (Nazário, Silva, Sobreiro, and Kimura, 2017; Avramov, Kaplanski and Levy, 2018).

3.3. Data

3.3.1. Data Sources

Data on S&P 500® levels come from several sources. From January 1928 to December 2020, the monthly open, high, low, and close levels of the index come from Yahoo! Finance. From 1871 to 1927, the average monthly S&P levels from the websites of Robert Shiller and Amit Goyal (see Welch and Goyal, 2008) are used as the open, high, low, and close levels, which limits the value of certain indicators. Monthly dividends used to calculate the monthly total S&P returns also come from the websites of Robert Shiller and Amit Goyal.

The monthly risk-free rate from July 1926 to December 2020 comes from the Wharton Research Data Services (WRDS) Fama-French Factors. Prior to July 1926, the risk-free rate from Amit Goyal's website is used. We also use WRDS for country indices under "World Indices by WRDS." Finally, individual stock data come from the Center for Research in Security Prices (CRSP), and data on Bitcoin are from Investing.com.

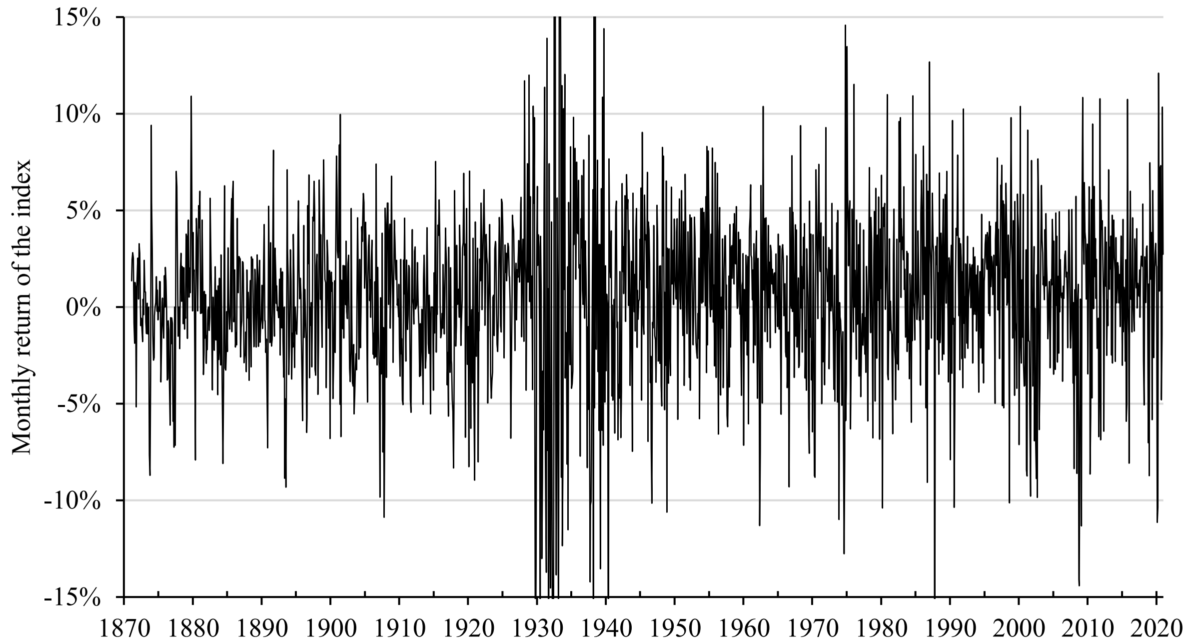
3.3.2. Variable Construction

The dependent variable and independent variables used in the probit model we develop in this paper are derived from the monthly S&P levels. The dependent variable, $Down_t$, is equal to one if the return of the stock market in month t is negative (a down month), and zero otherwise (an up month, as there are no flat months). This is based only on the change in the monthly close of the S&P levels, and does not consider any dividend payments. Of the 1799 monthly returns from February 1871 to December 2020, 80% are between -5% and 5%, 96% are between -10% and 10%, and 99% are between -15% and 15%. There are 757 down months and 1042 up months, meaning that on a monthly basis, the stock market provided a positive capital gains return approximately 58% of the time since 1871. Figure 3.1 is a graph of the monthly returns of the S&P 500® since 1871.

The independent variables in the model are derived from TA indicators. TA indicators fall into two broad categories, market and technical. There are two subcategories under market, breadth and sentiment, and there are four main subcategories under technical: trend, momentum, volatility, and volume. Technical analysts often use one or more indicators from multiple subcategories when making buy and sell decisions. Because our data consist only of price levels, this paper limits our independent variables to trend, momentum, and volatility TA indicators.

Figure 3.1. Monthly Returns of the Index

Data to calculate monthly market returns are from Yahoo! Finance and the websites of Robert Shiller and Amit Goyal.



To reduce data-snooping bias, the analysis in this paper applies the standard settings for five of the most commonly used TA indicators: Moving Averages (MA), Bollinger Bands (BB), the Moving Average Convergence / Divergence (MACD), the Relative Strength Index (RSI), and the Stochastic Oscillator (STO). MAs and the MACD are considered to be trend indicators; they help analysts to identify the direction of a trend—up, down, or sideways—in the prices of an asset, and often help with finding the beginning and end of trends. Trend indicators are usually lagging indicators. The RSI and STO are momentum indicators, meaning they help analysts evaluate the motion or strength of a given trend. Momentum indicators are usually leading. Finally, the BBs are volatility indicators and help analysts identify excitement in buying and selling. Volatility indicators are lagging indicators. From each of these five indicators (MA, BBs, MACD, RSI, and STO), multiple variables are created. This results in a matrix of variables for each TA indicator.

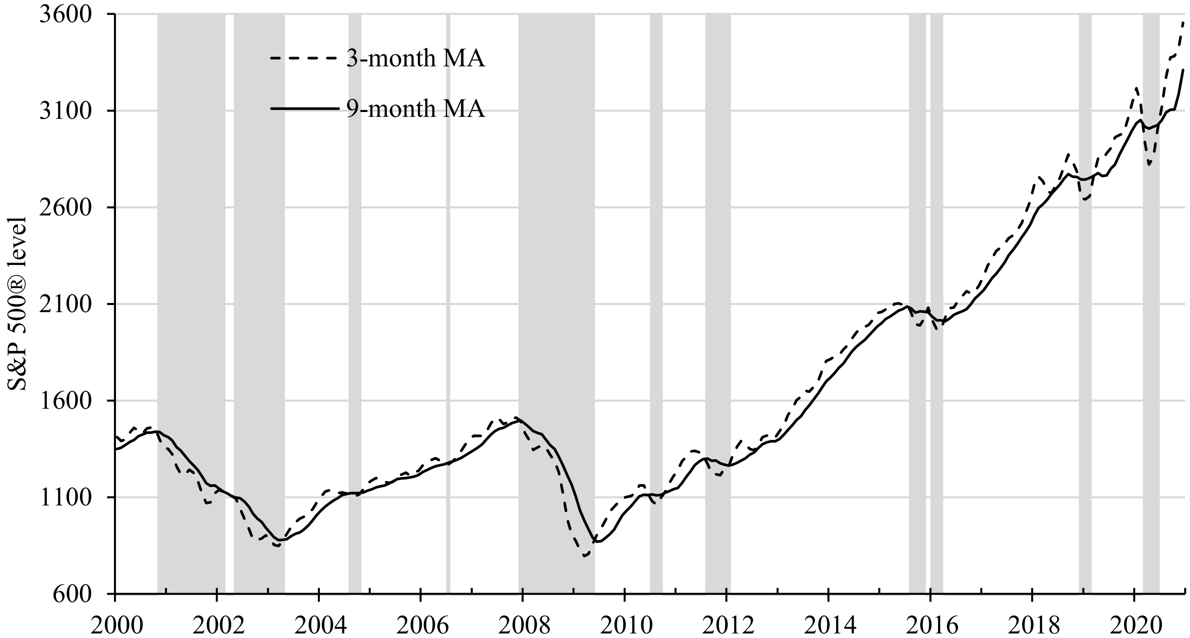
The idea behind creating multiple variables from each indicator is an attempt to mimic the decision-making process of technical analysts. TA is based on probabilities, and technical analysts want to be in a trade when the probability of that trade being profitable is high. On the other hand, technical analysts want close open positions when the probability of increased profits is low. To assess whether the probability is high or low, technical analysts not only consider whether a specific level has been breached on an indicator, but also how far the indicator is from the breach level, the change from the previous level of that indicator, and whether the indicators are speeding up or slowing down. Details on the variables can be found in Appendix A.

The first indicator, Moving Averages, consist of two (or more) simple MAs (SMA) of the closing monthly S&P level. One MA is denoted as the short MA, and the other is the long MA. Traditional research on MAs typically implements a MA crossover rule to generate buy and sell signals. This crossover rule says when the short MA crosses above (below) the long MA, that is a buy (sell) signal. Multiple papers have shown that trading strategies using these MA rules are able to generate higher returns than a standard buy-and-hold strategy (BLL; Han et al., 2013; and NRTZ). We follow NRTZ and use short MAs of 1-, 2-, and 3-month periods and long MAs of 9- and 12-month periods. Figure 3.2 is a subsample graph from 2000 to 2020 of the 3- and 9-month MAs. The results in this paper are based on the 3- and 9-month MAs, but results using other MAs are available from the author.

In addition to employing a MA crossover indicator (*MACI*) variable (similar to that employed by BLL and NRTZ) in our model, we also include the level of the short and long MAs, the change in the levels, and the rate of change in the levels. Dummy variables for the change and rate of change are also included in the model. Dummy variables are set equal to one if the current value of the variable is negative, and zero otherwise.

Figure 3.2. Short and Long Moving Averages

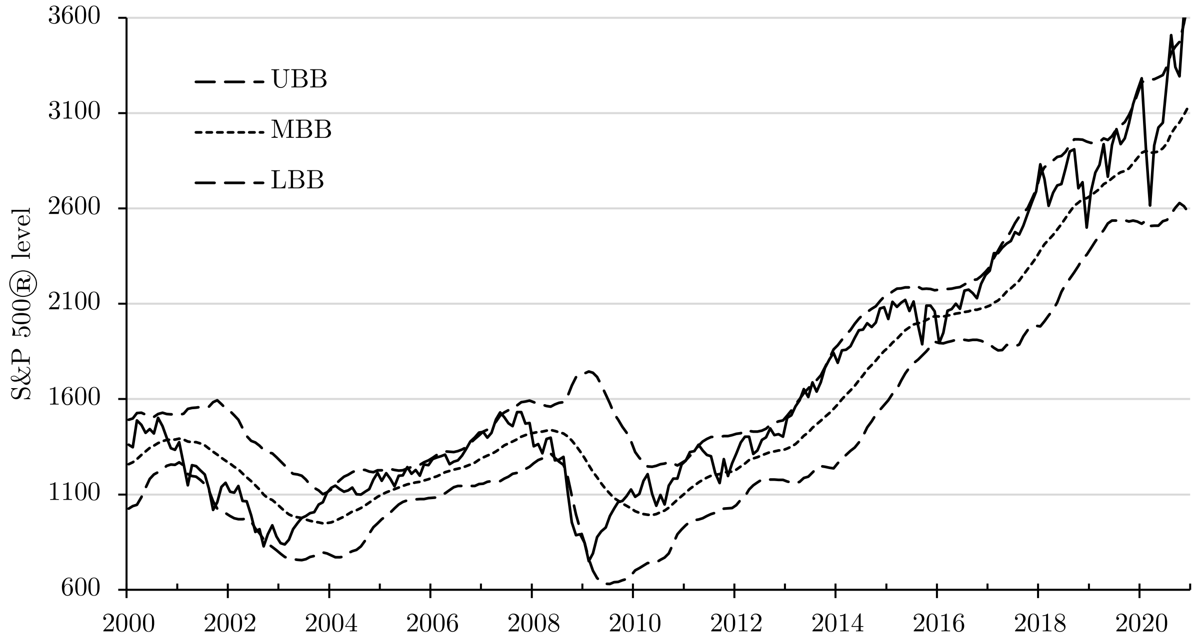
This graph shows the 3- and 9-month MAs from 2000 to 2020. The difference between the two MAs is traditionally used in research to determine buy and sell signals. When the dotted line (3-month MA) crosses above the solid line (9-month MA) a buy signal is generated. When the dotted line crosses below the solid line, a sell signal is generated. The gray vertical bars mark months when the short MA is below the long MA.



Nearly all TA indicators are dependent on some form of MAs. The second TA indicator, Bollinger Bands, is based on standard deviations from a MA line. Bollinger Bands contain three lines: the upper Bollinger Band (UBB), the middle Bollinger Band (MBB), and the lower Bollinger Band (LBB). The MBB is a MA of the closing price level of an asset, while the UBB and LBBs are a certain number of standard deviations away from the MBB. We utilize the traditional 20-period MA for the MBB and two standard deviations for the UBB and LBB (Bollinger, 1992). Figure 3.3 is a subsample graph from 2000 to 2020 of the Bollinger Bands around the S&P 500® index.

Figure 3.3. Bollinger Bands

This graph shows the Bollinger Bands around the S&P 500® from 2000 to 2020 using the traditional settings of 20, 2 (20-period MA for the middle Bollinger Band and 2σ for the upper and lower Bollinger Bands). The UBB and LBB are the dashed lines while the MBB is the dotted line. The solid line follows the monthly closing level of the S&P 500® index.

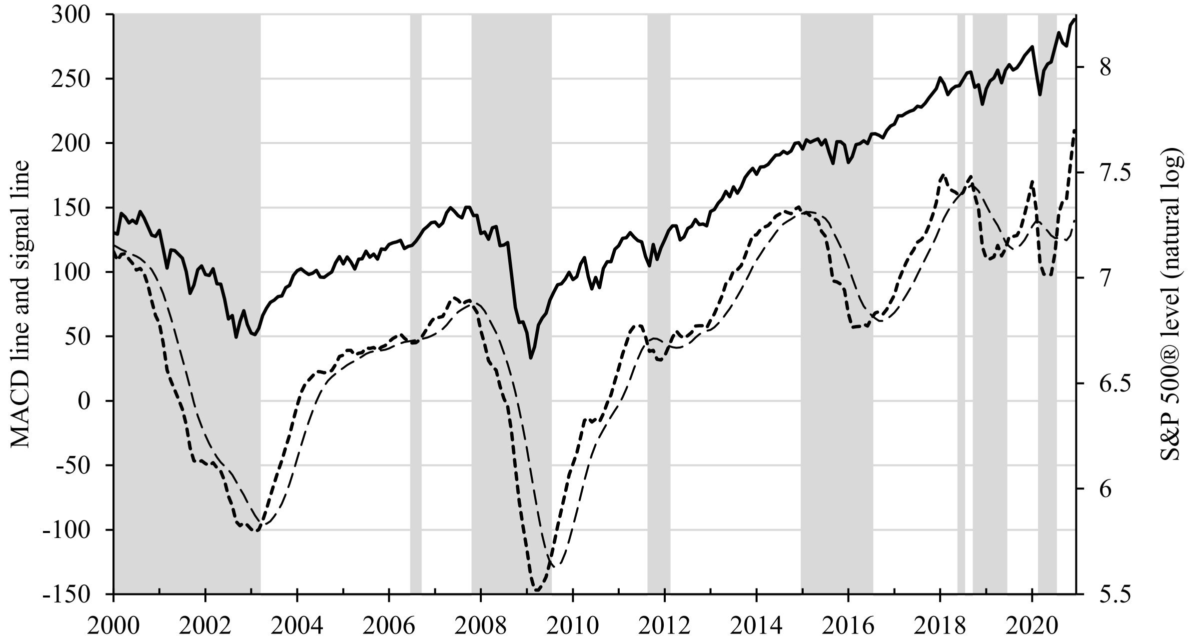


The third TA indicator used in our probit model is the MACD. The MACD was developed by Gerald Appel in the 1970's (Appel, 2005) and may be the most commonly used indicator by technical analysts. Like the BB, the MACD is a MA-based indicator. However, instead of using SMAs, the MACD uses exponential moving averages (EMA).

The MACD line is simply the difference between the short EMA and the long EMA. Traditionally, a trading signal is generated when the MACD line crosses a signal line, which is an EMA of the MACD line. The standard MACD indicator uses a 12-period EMA for the short MA, a 26-period EMA for the long MA, and a 9-period EMA for the signal line. A graph of the subperiod MACD is shown in Figure 3.4, overlayed on the natural log of the S&P 500® levels and periods where the MACD line has crossed below the signal line noted by gray vertical bars. For more details on the MACD, see Appel (2005).

Figure 3.4. The Moving Average Convergence-Divergence

This graph shows the MACD line and its signal line using 12-, 26-, and 9-period EMAs from 2000 to 2020. When the thick dotted MACD line crosses below the thin dashed signal line, generates a dummy sell-signal, marked by the gray vertical bars. The solid line is the natural log of the S&P 500® levels.

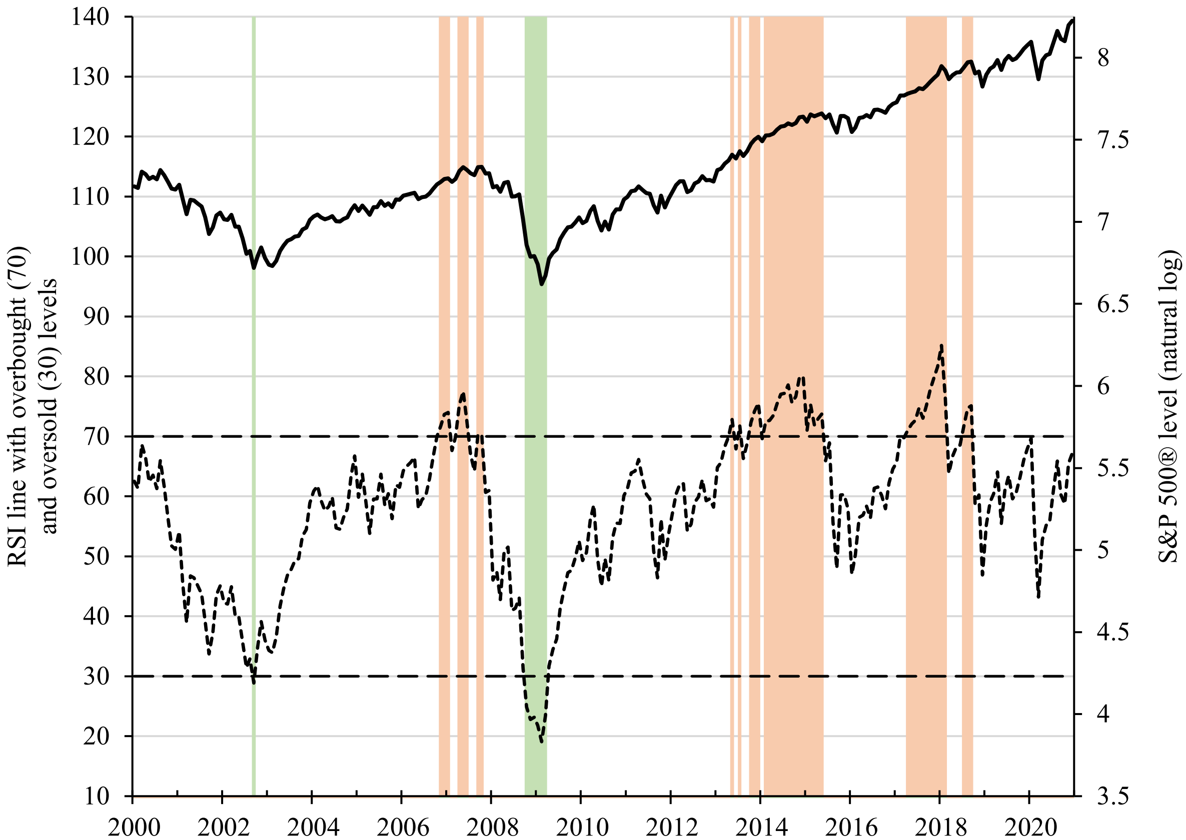


The RSI is fourth TA indicator in our model. The RSI was created by J. Welles Wilder and is detailed in his book *New Concepts in Technical Trading Systems* (Wilder, 1978). Similar to the BB and the MACD, the RSI uses MAs, but not MAs based on the closing level of an asset. Rather, the RSI is based on a Wilder's MA of the gains and losses. Details on calculating RSI can be found in Wilder (1978). We use the original setting developed by Wilder of a 14-period MA. Figure 3.5 contains a subsample graph of the RSI from 2000 to 2020.

The RSI oscillates between 0 and 100. Conventional settings for the RSI use 30 and 70 as overbought and oversold levels. In other words, when the RSI crosses above 70, technical analysts would prepare for a decline in the asset price or index level. While analysts would not necessarily short a stock when the RSI crosses above 70, they would certain be preparing to sell the stock if they held it in their portfolio; the latest point to sell would be when the RSI crosses below the 70 mark. Likewise, when the RSI crosses below 30, analysts would prepare for a rise in the stock price. A confirmed buy would be generated when the RSI crosses above 30.

Figure 3.5. The Relative Strength Index

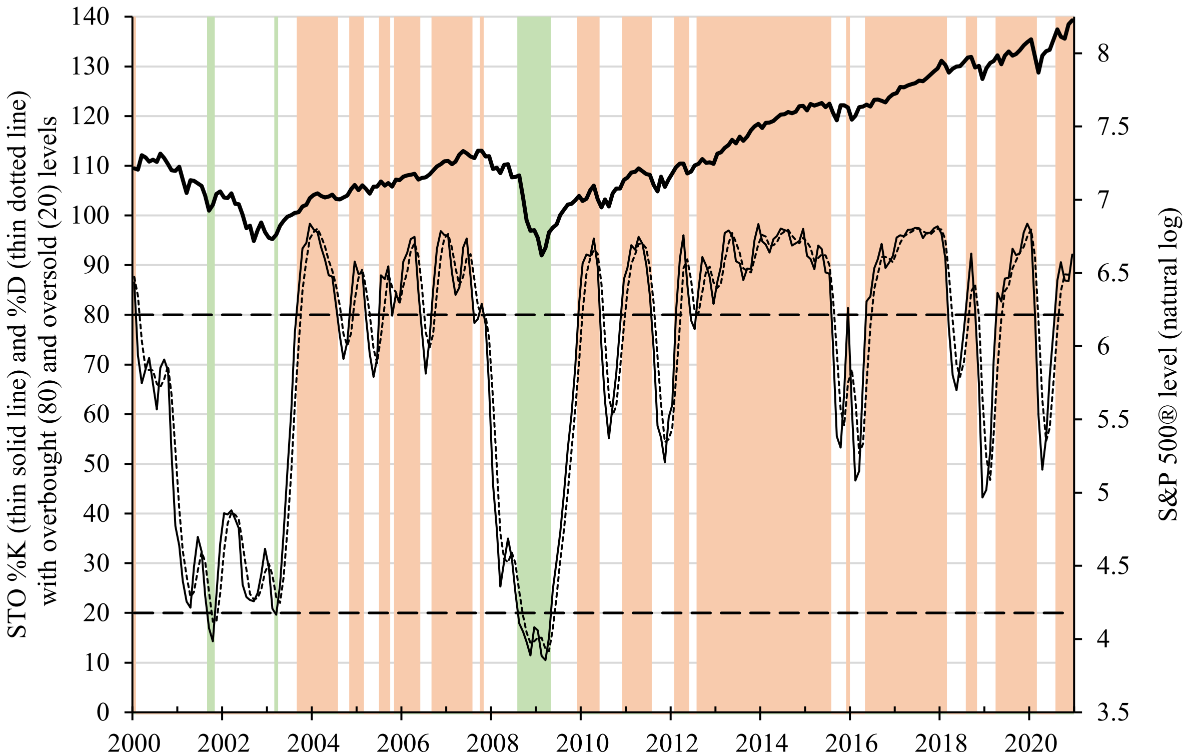
This graph shows the 14-period RSI line from 2000 to 2020. When the thick dotted line crosses below the thin solid line at 30, the asset is considered oversold. When the thick dotted line crosses above the thin dashed line at 70, the asset is considered overbought. These areas are marked by the green and orange vertical bars, respectively. The solid line is the natural log of the S&P 500® levels.



The final TA indicator used in our model is the STO. This indicator was designed by George Lane in the 1950s and compares the current closing price of an asset to recent past high and low prices (Lane, 1985; Murphy, 1999). Like the RSI, the STO oscillates between 0 and 100. However, overbought and oversold levels are set at 80 and 20, respectively. The default settings for STO are a 14, 3, 3, meaning the past 14 periods are used to generate the %K line, which is then smoothed by using a 3-period SMA. This smoothed line is known as the Slow %K. The signal line, known as %D, is a 3-period SMA of the Slow %K. Details on calculating STO can be found in Murphy (1999). A subsample graph of STO from 2000 to 2020 is found in Figure 3.6.

Figure 3.6. The Stochastic Oscillator

This graph shows the 14, 3, 3 STO from 2000 to 2020. When the thick dotted line crosses below the thin solid line at 30, the asset is considered oversold. When the thick dotted line crosses above the thin dashed line at 70, the asset is considered overbought. These areas are marked by the green and orange vertical bars, respectively. The solid line is the natural log of the S&P 500® levels.



3.4. Methodology

3.4.1. The Forecasting Model

The model we use is

$$\Pr(Down_{t+1} = 1) = \Phi(\beta_0 + \beta_{BB}\boldsymbol{BB}_t + \beta_{MA}\boldsymbol{MA}_t + \beta_{MACD}\boldsymbol{MACD}_t + \beta_{RSI}\boldsymbol{RSI}_t + \beta_{STO}\boldsymbol{STO}_t), \qquad (2)$$

where

Pr = the probability forecast of a stock market down month;

$Down_t$ = 1 if the return of the stock market in month t is negative, or 0 otherwise (the return of the stock market in month t is not negative);

Φ = the cumulative normal probability density function;

$\boldsymbol{BB}_t$ = a matrix of variables from the Bollinger Bands;

$\boldsymbol{MA}_t$ = a matrix of variables from the 3- and 9-month Moving Averages;

$\boldsymbol{MACD}_t$ = a matrix of variables derived from the Moving Average Convergence / Divergence;

$\boldsymbol{RSI}_t$ = a matrix of variables derived from the Relative Strength Index

$\boldsymbol{STO}_t$ = a matrix of variables derived from the Stochastic Oscillator

Using our probit model, we estimate the coefficients for *BB, MA, MACD, RSI* and *STO* using data from August 1871 to November 1880, known as the in-sample period or historical estimation period. The coefficients are then fitted to the December 1880 values to forecast the probability of a down month in the stock market in January 1881—the OOS period. This procedure is repeated for the entire sample period by adding one month of data at a time to the historical estimation period until a total of 120 months (10 years) are used for the in-sample period. This takes place in July 1871. After that date, the last month of data are dropped for each successive regression. Thus, for each successive month, new OOS forecasts of stock market corrections are obtained through January 2021. The coefficients from December of every 20 years are displayed in Table 3.1.

Table 3.1. Significance of Coefficients from Probit Model Estimations

The table reports the estimated coefficients of ***BB***, ***MA***, ***MACD***, ***RSI***, and ***STO*** and the Pseudo R^2s from the model $\Pr(Down_{t+1} = 1) = \Phi(\beta_0 + \beta_{BB}\boldsymbol{BB}_t + \beta_{MA}\boldsymbol{MA}_t + \beta_{MACD}\boldsymbol{MACD}_t + \beta_{RSI}\boldsymbol{RSI}_t + \beta_{STO}\boldsymbol{STO}_t)$. They are listed for December in 20-year intervals, except for the first period, which is 10 years). Significance at the 10%, 5%, and 1% levels are marked by *, **, and *** respectively.

Variable	1900	1920	1940	1960	1980	2000	2020
Intercept	-201.27**	89.22	89.37***	-887.58***	69.86	-53.30	1477.98***
STBB	-0.00	0.10*	0.13***	-0.96***	0.07	-0.08	-0.23
SMBB	-0.08	0.67*	-0.16*	1.01	0.26	-0.14	4.58***
Δ_*STBB*	-3.10***	5.70***	-0.20	5.13	-0.71	1.08	7.33*
Δ_*SMBB*	2.70*	-8.95***	0.66	-4.36	0.42	2.37	-0.26
roc_STBB	-0.45	0.11	-0.03	-0.84	-0.48*	-0.77	-4.49***
roc_SMBB	0.55	0.43	-0.37**	2.91***	0.62	0.44	3.64***
1.*STBB*_Δ_*i*	2.03***	-1.52	-0.57	-1.64	-0.26	0.86	-4.96***
1.*SMBB*_Δ_*i*	4.42***	-2.28	-1.04	6.48***	0.65	-1.38*	-2.77**
1.*SLBB*_Δ_*i*	0.50	0.77	0.82	-2.73*	0.25	0.36	1.20
1.*STBB_roc_i*	0.22	-2.11	-0.14	-0.02	-0.45	0.81	-21.19***
1.*SMBB_roc_i*	1.86	-1.68	-3.59***	2.71	1.68	-2.61**	-5.83***
1.*SLBB_roc_i*	0.56	-1.83	1.70	12.36***	-0.81	1.46	5.58***
SPMA_3	1.73**	-0.39	-1.06***	18.93***	-0.93	0.18	-10.11***
SPMA_9	0.13	-1.01**	0.18	-10.71***	-0.17	0.54	-9.29***
Δ_*SMA*	-0.36	-0.56	-0.37***	7.25***	0.46	0.36	1.17
roc_SMA	-0.39	1.12**	0.47***	-5.12***	-0.15	-0.18	-1.60***
1.*SMACI*	-1.55**	0.06	-1.04	-10.21***	-0.03	0.39	-8.08***
1.*SMACI*_Δ	0.45	2.84*	-0.76	3.70**	0.69	-0.81	-0.02
1.*SMACI_roc*	-0.54	0.76	1.86**	-3.80***	1.21**	0.04	-3.37***
SMACD	-0.25	3.21*	0.07	-29.96***	1.08	0.84	-12.09***
SMACD_sig	-0.32	-1.27	0.00	25.11***	-0.71	-0.40	8.38***
Δ_*SMACD*	2.01	-6.68	0.02	-69.06***	-2.00	8.15*	-70.76***
roc_SMACD	-1.76	1.38	-1.09***	49.67***	-1.02	1.80	80.45***
1.*SMACD_i*	0.41	-4.70***	3.70***	-5.59***	0.80	0.99	-0.62
1.*SMACD*_Δ_*i*	1.40*	1.69	0.22	-3.7***	1.09	0.01	1.08
1.*SMACD_roc_i*	-0.65	-1.93**	-0.76	-2.59**	-0.60	-0.61	4.83***

Table 3.1. (continued)

Variable	1900	1920	1940	1960	1980	2000	2020
RSI	0.30	-0.47***	-0.01	0.49	0.08	0.01	0.26**
Δ_RSI	0.99**	0.11	-0.40**	0.79**	-0.22	0.20	-3.72***
roc_RSI	-0.16	0.32*	-0.13	0.34	0.26	-0.09	3.46***
1.RSI_i	-0.03	-2.14**	-1.53		1.73		
2.RSI_i	-0.25	0.69	0.76	2.85***		-1.09	-1.97*
1.RSI_Δ_i	4.10***	-0.58	-2.87***	-9.28***	0.17	-0.24	-7.41***
1.RSI_roc_i	3.48***	-2.25	-2.84**	21.77***	0.10		-27.04
STO_K	-11.03	-7.18	31.12***	1.87	1.99	-6.05	153.77***
STO_D	10.56	13.14	-28.09***	48.76***	-3.75	8.57	-86.40**
Δ_STO	17.40**	19.53*	-50.71***	80.12***	12.40	9.14	23.38
roc_STO	-3.83	-21.66*	47.07***	-103.83***	-22.00**	-11.90	-34.14*
1.STO_K_i	-0.88	0.97	0.17	-4.74	-0.96		
2.STO_K_i	-0.54	-3.85**	-5.74***	2.00**	0.75	0.82	-7.60***
1.STO_D_i	-0.34	0.50	-3.07**	12.19**	1.29		
2.STO_D_i	-0.22	-1.14	1.69	-2.09	-1.50**	-1.20	-0.10
1.STO_i	-0.94*	3.46***	0.83	5.36***	0.35	-0.22	5.29***
1.STO_d_i	1.33*	-0.69	-1.56**	4.18***	1.47**	-0.32	3.74***
1.STO_roc_i	0.41	-0.18	2.85***	0.83	-0.61	-0.23	4.65***
Pseudo R^2	0.431	0.543	0.5261	0.6779	0.3578	0.2666	0.7458

3.4.2. Portfolio Management

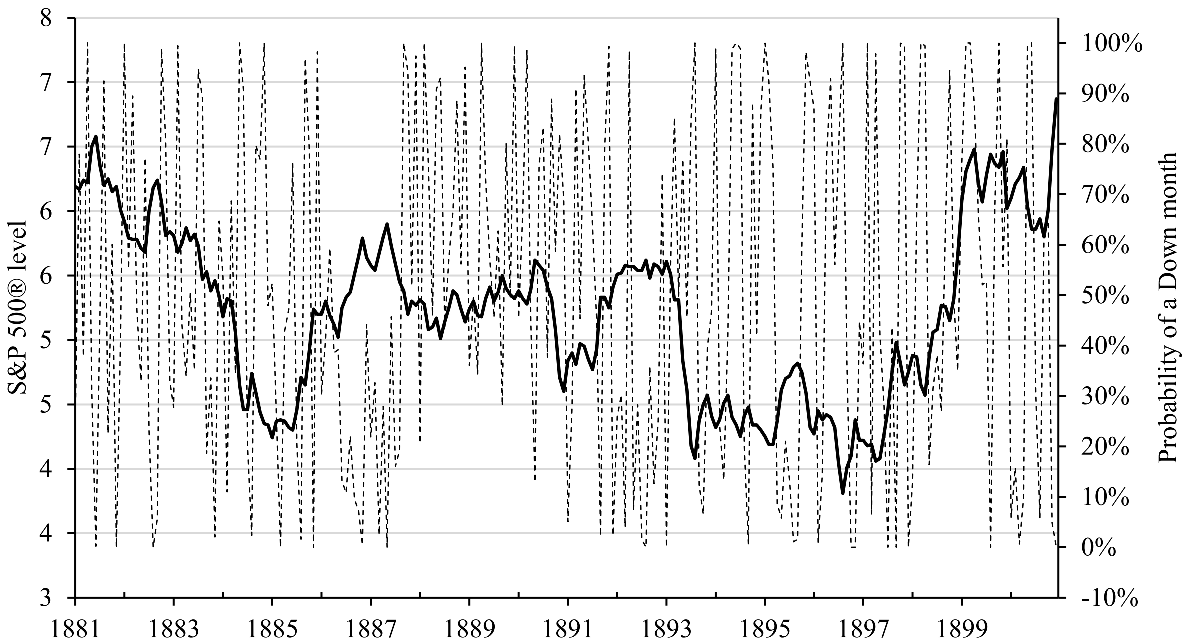
The forecasts obtained from the fitted coefficients are used to create a market-timing strategy for a mean-variance, long-only investor. We follow RS and compare two simulated investment strategies: 1) the benchmark buy-and-hold strategy which invests in a total return S&P 500® index fund (includes dividends and capital gains) at the beginning of January 1881 and 2) a market-timing strategy that alternates the investor's portfolio between the S&P 500® tracking fund (no dividends) and cash. We take a conservative approach to the market-timing returns by assuming that the market-timing investor earns no return when the portfolio is in cash, and only receives capital gains returns when the portfolio is in the index fund.

The movement of the investment in the market-timing strategy from cash to the fund and vice versa is directed by the probit model's forecasted probability of a down month in the market. When the probability of a down month in the model's forecast surpasses a specified threshold, which we label *X*, the investment is moved out of the index fund and into cash. Otherwise, if the forecasted probability is below *X*, our investment remains invested in or is moved back into the S&P index fund. We test several levels of *X* to compare the results: 40%, 50%, 60%, and 70%. Figure 3.7 shows the forecasted probabilities of a correction one month later.

Figure 3.7. Forecasted Probability of a Down Month and the S&P 500®

The following figures show the S&P level (solid line) and the forecasted probability of a down month (dotted line) in 20-year increments. Data to calculate market down months are from Yahoo! Finance and the websites of Robert Shiller and Amit Goyal.

A: 1881 to 1900



B: 1901 to 1920

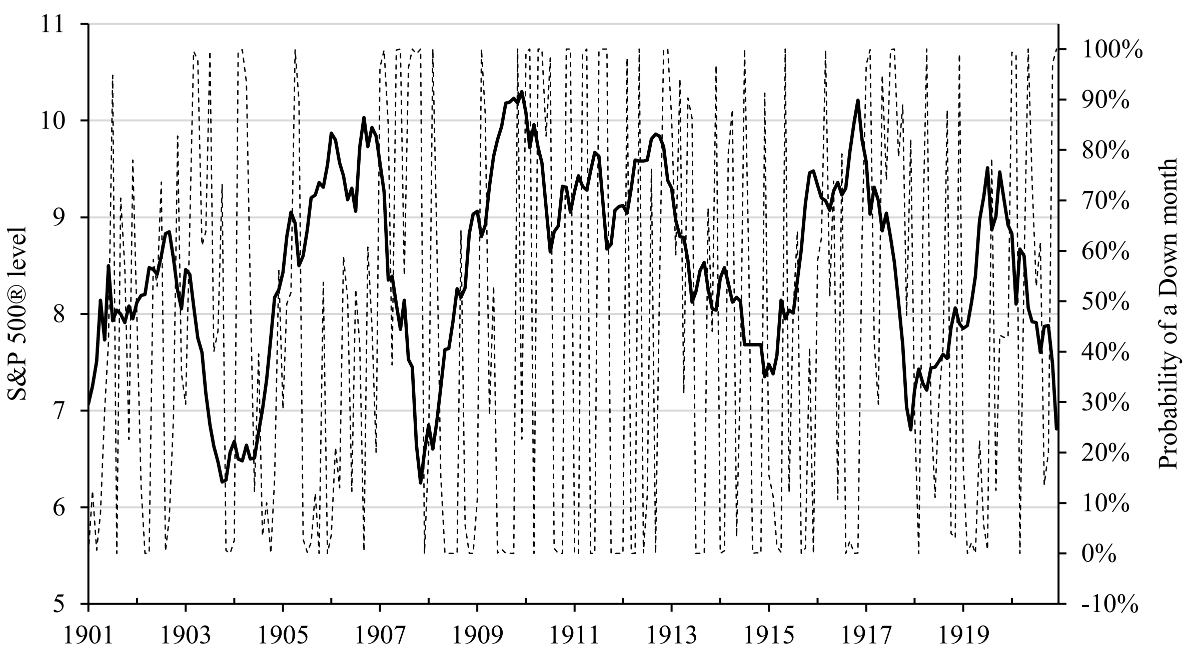
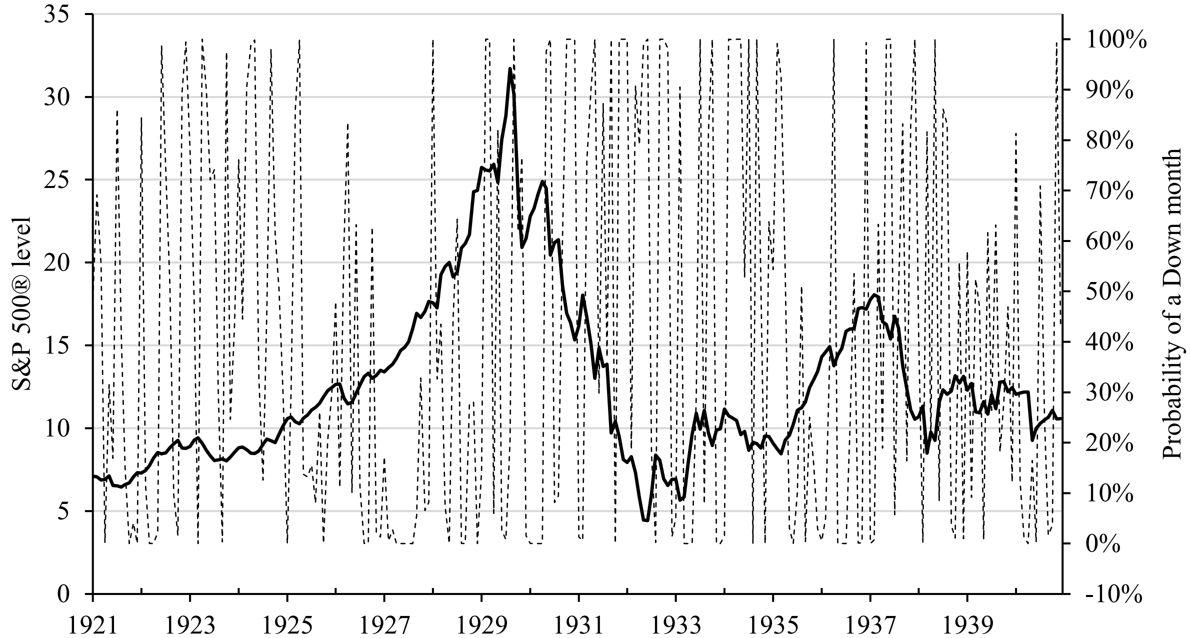


Figure 3.7. Forecasted Probability of a Down Month and the S&P 500® (continued)

C: 1921 to 1940



D: 1941 to 1960

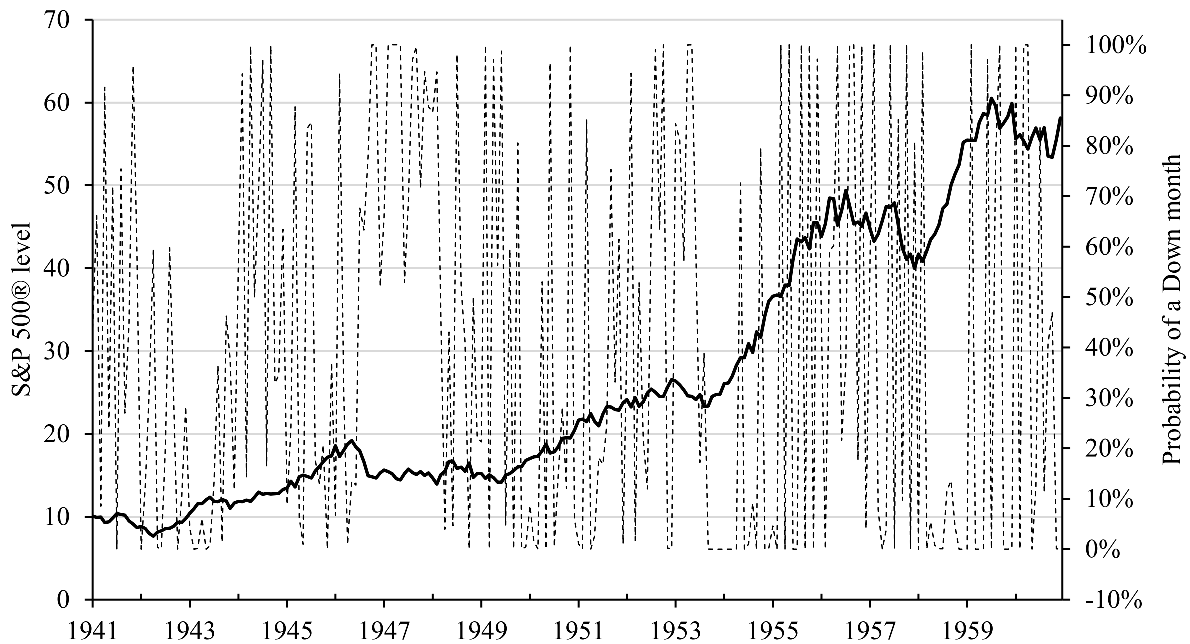
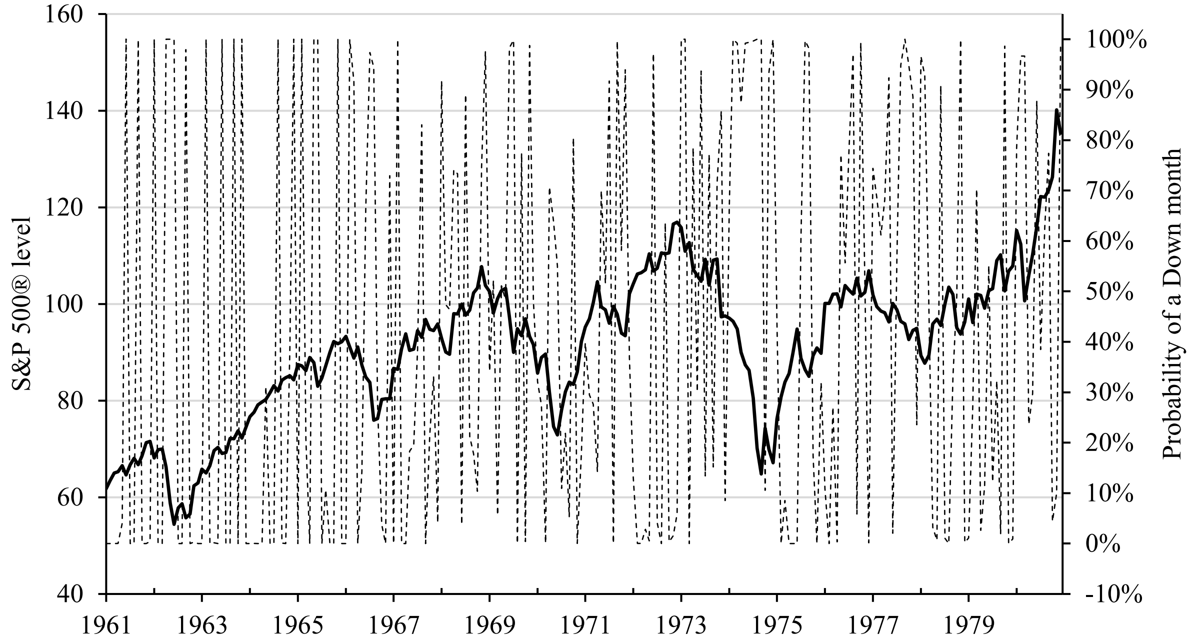


Figure 3.7. Forecasted Probability of a Down Month and the S&P 500® (continued)

E: 1961 to 1980



F: 1981 to 2000

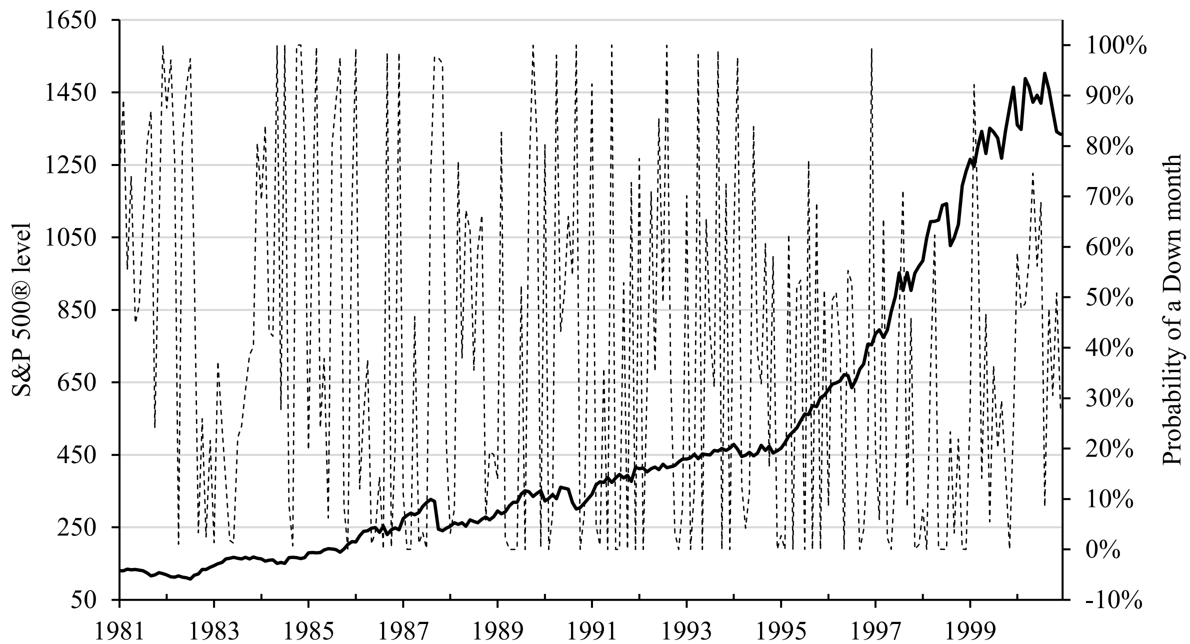
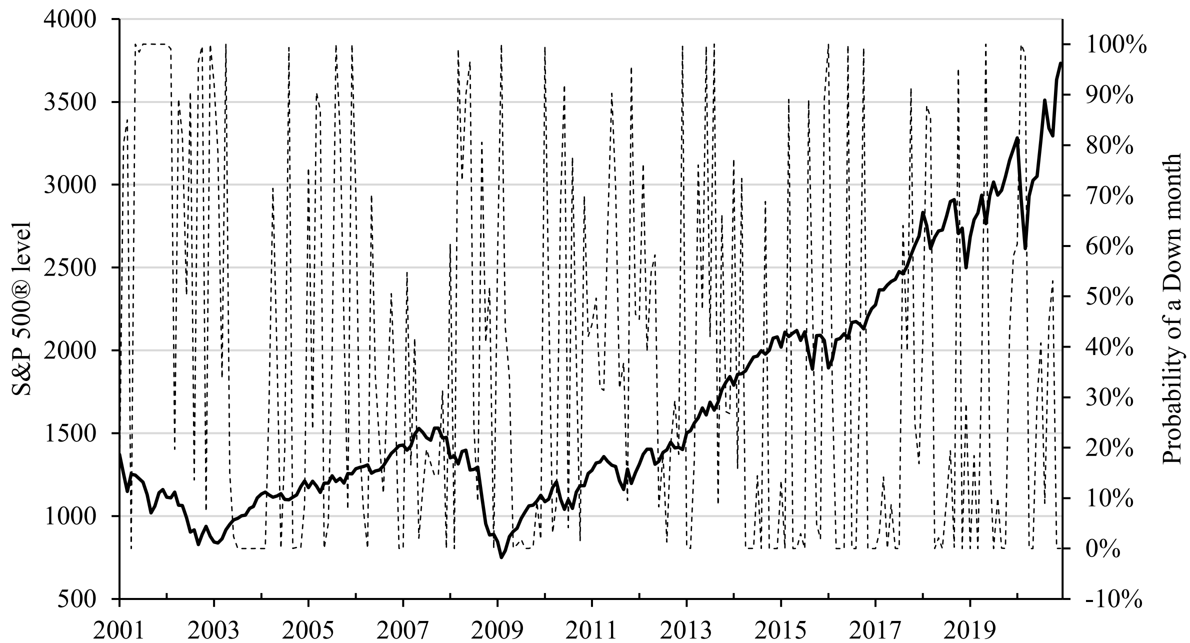


Figure 3.7. Forecasted Probability of a Down Month and the S&P 500® (continued)

G: 2001 to 2020



3.4.3. Transaction Costs

In addition to being conservative with the market-timing investor's returns, we also applied a conservative approach to transaction costs. We assume the buy-and-hold investor has no transaction costs, since that portfolio is always fully invested in the total return fund. However, the market-timer has a transaction cost for each move into and out of the index fund that reduces the overall return of the portfolio.

Transaction costs are the result of both the bid-ask spread and commission costs. Several studies have estimated transaction costs (see Roll, 1984; Bessembinder, 2003; Lesmond, Ogden, and Trzcinka, 1999; Corwin and Schultz, 2012; Holden, 2009; and Abdi and Ranaldo, 2017, among others). Other research has noted the effect transaction costs have on investors' portfolios (see Barber and Odean, 2000; Engle, Ferstenberg, and Russell, 2008; and Hilliard and Hilliard, 2011).

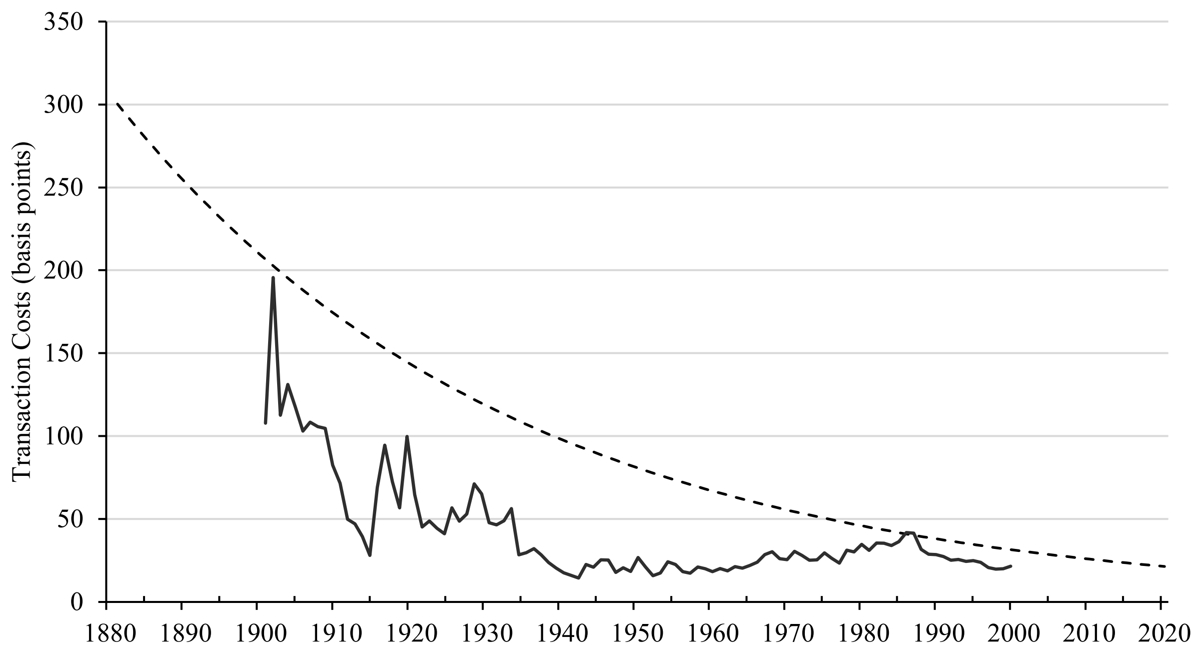
We attempt to model realistic yet conservative transaction costs. Jones (2002) estimates transactions costs from 1900 to 2000. His results are similar to other transaction cost literature (Barber and Odean, 2000; Abdi and Ranaldo, 2017 and others). To simplify our transaction costs, we assume transaction costs (half-spread and commission) to be adjusted annually based on the following equation:

$$\text{Transaction\_Costs} = 0.0306 \times \exp(-0.019 \times (\text{year} - 1880)). \tag{3}$$

By using this equation, transaction costs are approximately 300 basis points in 1881, a conservative estimate by any standard, and 20 basis points in 2020, again a very conservative estimate. Figure 3.8 compares Jones's (2002) transaction cost estimates using NYSE data and our simplified transaction cost model.

Figure 3.8. Comparison of Transaction Costs

This graph replicates Figure 6 in Jones (2002) and overlays it with our estimate of transaction costs.



While our transaction costs are higher than Jones's (2002) estimates and almost all other estimates in the literature, we wanted to be conservative in our market-timing approach. In reality, today's transaction costs are much lower since nearly all broker/dealers eliminated commissions on equity transactions in 2019. Additionally, spreads on S&P 500® stocks are averaging around 0.05 basis points (0.13 basis points for the market-weighted average), so if transaction costs are half the bid-ask spread, then the current impact of transaction costs on market-timing methods are just a fraction of a basis point, far below historical transaction cost levels.

3.5. Model Performance

3.5.1. Market-timing Results

The results of the two simulated investment strategies—the baseline buy-and-hold strategy and the probit-based market-timing strategy—are detailed in Table 3.2. The table shows the terminal value of $1 invested in each strategy for various investment timeframes. For example, a $1 investment in the S&P index fund in January 1881 grew to $220,461 by December 2020; that is an annual compound return of nearly 9.2%. However, using a market-timing strategy based on the probit model, the $1 invested in January 1881 grew to between $2.76 million and $8.90 million by December 2020, depending on which *X* threshold was specified as the probability cutoff. In all subperiods, the market-timing strategy outperforms the buy-and-hold strategy by an economically significant amount, no matter which probability level is specified. Our model does not appear to be spurious.

The outperformance of the market-timing model is greatest from 1921 to 1940. This is likely due to the probit model getting the market-timing investor out of the market prior to major down months and back into the market prior to major up months. The weakest timeframe of the market-timing model was from 1981 to 2000. While the largest single-day percentage drop occurred during the period (October 19, 1987), the market-timer was directed to pull their portfolio out of the market prior to August 1987 and stay out through November 1987. Most of the 1981 to 2000 period was a steady march upward, resulting in numerous months where the probit model directed the market-timer to withdraw funds from the market, but the market return was positive.

Table 3.2. Market-Timing Strategies Results

The table reports the terminal wealth and compound monthly and annual returns of various investment strategies over the entire sample period and three subperiods. The market-timing strategies invest in an S&P 500® index fund if the OOS probability of a market correction based on the probit model is less than threshold at the top of the column; otherwise, the funds in cash and are assumed to have no return. "Terminal wealth" is the value at end of the period of a $1 investment at the beginning of the period.

Measure	Buy & Hold	$X = 0.40$	$X = 0.50$	$X = 0.60$	$X = 0.70$
A. Jan 1881-Dec 2020					
Terminal wealth	$220,461	$6,471,199	$8,904,378	$4,151,552	$2,755,802
Monthly Comp. Rtn.	0.74%	0.94%	0.96%	0.91%	0.89%
Annual Comp. Rtn.	9.19%	11.85%	12.11%	11.50%	11.17%
B. Jan 1881-Dec 1900					
Terminal wealth	$2.98	$7.23	$7.19	$6.22	$5.62
Monthly Comp. Rtn.	0.46%	0.83%	0.83%	0.76%	0.72%
Annual Comp. Rtn.	5.62%	10.39%	10.37%	9.57%	9.02%
C. Jan 1901-Dec 1920					
Terminal wealth	$2.84	$10.97	$12.64	$11.67	$9.66
Monthly Comp. Rtn.	0.44%	1.00%	1.06%	1.03%	0.95%
Annual Comp. Rtn.	5.35%	12.72%	13.52%	13.07%	12.01%
D. Jan 1921-Dec 1940					
Terminal wealth	$4.65	$248.56	$286.12	$235.73	$143.69
Monthly Comp. Rtn.	0.64%	2.32%	2.38%	2.30%	2.09%
Annual Comp. Rtn.	7.99%	31.76%	32.69%	31.41%	28.20%
E. Jan 1941-Dec 1960					
Terminal wealth	$15.32	$27.55	$23.25	$22.87	$22.19
Monthly Comp. Rtn.	1.14%	1.39%	1.32%	1.31%	1.30%
Annual Comp. Rtn.	14.62%	18.03%	17.04%	16.94%	16.76%
F. Jan 1961-Dec 1980					
Terminal wealth	$4.84	$29.06	$29.81	$29.16	$21.98
Monthly Comp. Rtn.	0.66%	1.41%	1.42%	1.42%	1.30%
Annual Comp. Rtn.	8.20%	18.35%	18.50%	18.37%	16.71%
G. Jan 1981-Dec 2000					
Terminal wealth	$18.38	$31.33	$40.15	$36.22	$42.30
Monthly Comp. Rtn.	1.22%	1.45%	1.55%	1.51%	1.57%
Annual Comp. Rtn.	15.67%	18.79%	20.28%	19.66%	20.59%
H. Jan 2001-Dec 2020					
Terminal wealth	$4.11	$21.12	$27.84	$21.73	$18.69
Monthly Comp. Rtn.	0.59%	1.28%	1.40%	1.29%	1.23%
Annual Comp. Rtn.	7.32%	16.47%	18.10%	16.64%	15.76%

Another market downturn of interest to current investors is the Corona Virus Crash, beginning in February 2020 and ending in March 2020. From its peak of 3386.15 on February 19, 2020, the S&P 500® fell to a low of 2237.33 on March 23, 2020. That was a decline of almost 34% in just over a month. That decline was completely recovered by August 18, 2020, for a gain from of over 51% from the March low. For the buy-and-hold investor, the 1-year holding period return (HPR) from the end of August 2019 to the end August 2020 was 20%. But the 1-year HPR for the market-timer using a 50% threshold was 143%. This outperformance was due to the probit model forecasting the probability of a down month each month from December 2019 to March 2020 to be higher than 50%. Although the market-timing portfolio missed out on a 4% gain in December and January, it benefitted from missing out on the February and March drop. The forecast for April dropped below the 50% threshold, so the market-timing portfolio profited handsomely over the next several months.

3.5.2. Testing Market-timing Performance

There are several tests to evaluate the market-timing ability of a particular strategy. A simple first step is to look at the summary statistics of the portfolio monthly returns. Along with the summary statistics, we conduct T-tests to compare the monthly buy-and-hold returns to the monthly returns of the market-timing portfolios.

Table 3.3 presents monthly return summary statistics and T-test results of the portfolios for the entire period from 1881 to 2020. The average monthly return of the buy-and-hold portfolio is less than that of each of the market-timing portfolios. The difference between the monthly returns of the buy-and-hold portfolio and each market-timing portfolio is statistically significant, as shown by the T-test results.

Table 3.3. Summary Statistics of Monthly Returns & T-test Results

This panel reports the summary statistics of the monthly returns for the buy-and-hold portfolio and the market-timing portfolios.

Variable	B&H	X = 40	X = 50	X = 60	X = 70
N	1,680	1,680	1,680	1,680	1,680
Mean	0.8489%	1.4287%	1.4747%	1.4312%	1.3708%
Median	1.0148%	0.0000%	0.1013%	0.2854%	0.3915%
1st percentile	-13.0435%	-4.4028%	-6.0393%	-6.7877%	-7.4727%
99th percentile	11.8603%	11.3650%	11.5183%	11.5183%	11.5183%
Std. Dev.	0.0478	0.0314	0.0334	0.0349	0.0364
Skewness	0.1758	3.2574	2.5998	2.1685	1.7174
Kurtosis	12.3596	36.9414	29.8082	25.6384	22.8841
Timer – B&H		0.5798%	0.6259%	0.5823%	0.5219%
T-stat		7.4435	8.6855	8.4910	8.0173

Another simple test is to examine excess returns—the return an investment strategy provides to an investor beyond the risk-free rate. Summary statistics for the excess returns of each portfolio are presented in Table 4, not only for the entire period, but all for each subperiod. During the entire sample period and the seven subperiods, the average monthly excess return of the buy-and-hold strategy (which is the excess return of the market) is less than the monthly excess return of the market-timing strategies for every level of *X*. Additionally, the standard deviation of the buy-and-hold strategy is greater than all the probit-directed market-timing strategies. Thus, using the probit market-timing strategies, an investor could have generated higher returns with lower risk.

Table 3.4. Summary Statistics of Excess Returns

The panel reports the summary statistics for the monthly excess return of each portfolio over the entire sample period and three subperiods at different thresholds for the probability of down month.

Measure	Buy & Hold	$X = 0.40$	$X = 0.50$	$X = 0.60$	$X = 0.70$
A. Jan 1881-Dec 2020					
Observations	1680	1680	1680	1680	1680
Mean	0.5636%	1.1434%	1.1894%	1.1459%	1.0855%
Standard Deviation	0.0479	0.0317	0.0336	0.0350	0.0365
B. Jan 1881-Dec 1900					
Observations	240	240	240	240	240
Mean	0.1723%	0.5140%	0.5159%	0.4574%	0.4163%
Standard Deviation	0.0310	0.0192	0.0212	0.0223	0.0230
C. Jan 1901-Dec 1920					
Observations	240	240	240	240	240
Mean	0.1719%	0.6975%	0.7634%	0.7318%	0.6555%
Standard Deviation	0.0348	0.0191	0.0223	0.0231	0.0245
D. Jan 1921-Dec 1940					
Observations	240	240	240	240	240
Mean	0.8252%	2.3151%	2.3791%	2.3084%	2.1182%
Standard Deviation	0.0830	0.0577	0.0583	0.0602	0.0633
E. Jan 1941-Dec 1960					
Observations	240	240	240	240	240
Mean	1.1110%	1.3200%	1.2577%	1.2552%	1.2447%
Standard Deviation	0.0380	0.0259	0.0292	0.0307	0.0314
F. Jan 1961-Dec 1980					
Observations	240	240	240	240	240
Mean	0.3010%	0.9991%	1.0146%	1.0071%	0.8927%
Standard Deviation	0.0423	0.0259	0.0277	0.0283	0.0300
G. Jan 1981-Dec 2000					
Observations	240	240	240	240	240
Mean	0.7726%	0.9464%	1.0570%	1.0225%	1.0908%
Standard Deviation	0.0416	0.0273	0.0293	0.0322	0.0330
H. Jan 2001-Dec 2020					
Observations	240	240	240	240	240
Mean	0.5786%	1.1991%	1.3259%	1.2266%	1.1676%
Standard Deviation	0.0448	0.0261	0.0296	0.0313	0.0327

3.5.2.1. The Henriksson-Merton Test

While the results in Table 3.3 and Table 3.4 support the performance of the probit model, more formal tests make the case even stronger. The first formal test, the Henriksson-Merton (HM) test, proposed in Merton (1981) and Henriksson and Merton (1981), evaluates the excess returns of the market-timing strategy against the excess returns of the buy-and-hold investment strategy during market "up" months and "down" months. The HM model can be written as,

$$R_{pt} - R_{ft} = \alpha + \beta_1 Up_t + \beta_2 Down_t + \varepsilon_t, \tag{4}$$

where

R_{pt} = the return of the market-timing portfolio in month t;

R_{ft} = the risk-free rate of return;

Up_t = the max($R_{mt} - R_{ft}$, 0), with R_{mt} being the return of the buy-and-hold portfolio;

$Down_t$ = the min($R_{mt} - R_{ft}$, 0).

Equation (3) estimates the beta of the market-timing strategy in forecasted "up" months, β_1, and "down" months, β_2. If $\beta_1 - \beta_2 > 0$, then the market-timing strategy can be considered successful. Table 3.5 documents the results of the of the HM tests. For the overall timeframe and each subperiod at every level of X, $\beta_1 - \beta_2$ is statistically significant, suggesting the strong presence of successful market timing.

3.5.2.2. The Cumby-Modest Test

A second common test to evaluate the market-timing ability of a proposed strategy is the Cumby-Modest (CM) test proposed by Cumby and Modest (1987). The CM test compares the excess returns of the buy-and-hold portfolio during forecasted "up" months to the excess returns of the buy-and-hold portfolio during forecasted "down" months. If no difference exists, the forecasting ability of the probit model is suspect. The formal CM model is:

$$R_{mt} - R_{ft} = \alpha + \beta Up_t + \varepsilon_t, \tag{5}$$

where

R_{mt} = the return of the buy-and-hold index portfolio in month t;

R_{ft} = the risk-free rate of return;

Up_t = 0 if the probit model forecast a correction in month t+1 and 1 otherwise.

Table 3.5. Henriksson-Merton Test of the Probit Forecast Model

The table reports the value of the coefficients from the regression $R_{pt} - R_{ft} = \alpha + \beta_1 Up_t + \beta_2 Down_t + \varepsilon_t$, with standard errors ($F$-statistics for $\beta_1 - \beta_2$) reported in parentheses. Significance at the 10%, 5%, and 1% levels are marked by *, **, and *** respectively.

	1881-2020	**1881-1900**	**1901-1920**	**1921-1940**	**1941-1960**	**1961-1980**	**1981-2000**	**2001-2020**
N	1680	240	240	240	240	240	240	240
				X = 0.40				
α	-0.0033***	-0.0037***	-0.0017	-0.0028	-0.0001	-0.0010	-0.0029*	-0.0023
	(0.0005)	(0.0011)	(0.0012)	(0.0019)	(0.0016)	(0.0014)	(0.0017)	(0.0016)
β_1	0.9042***	0.8699***	0.7746***	0.9735***	0.8311***	0.8170***	0.7951***	0.8042***
	(0.0139)	(0.0425)	(0.0451)	(0.0276)	(0.0469)	(0.0418)	(0.0498)	(0.0470)
β_2	0.0902***	0.0597	0.0742*	0.0940***	0.2015***	0.1322***	0.1682***	0.0699*
	(0.0138)	(0.0415)	(0.0380)	(0.0292)	(0.0518)	(0.0392)	(0.0472)	(0.0397)
β_1–β_2	0.8140***	0.8102***	0.7004***	0.8795***	0.6296***	0.6848***	0.6269***	0.7343***
	(1294.43)	(128.33)	(96.91)	(374.94)	(54.82)	(101.23)	(101.59)	(101.59)
R^2	0.7520	0.7019	0.6375	0.8568	0.6841	0.6934	0.6104	0.6174
				X = 0.50				
α	-0.0034***	-0.0033**	-0.0032***	-0.0026	0.0005	-0.0028**	-0.0047***	-0.0011
	(0.0005)	(0.0011)	(0.0010)	(0.0018)	(0.0016)	(0.0013)	(0.0015)	(0.0016)
β_1	0.9743***	0.9389***	1.0088***	0.9940***	0.8857***	0.9381***	0.9557***	0.9027***
	(0.0131)	(0.0433)	(0.0387)	(0.0262)	(0.0468)	(0.0380)	(0.0438)	(0.0472)
β_2	0.1394***	0.1519***	0.1100***	0.1069***	0.3886***	0.1298***	0.1740***	0.1912***
	(0.0130)	(0.0423)	(0.0326)	(0.0276)	(0.0516)	(0.0356)	(0.0415)	(0.0399)
β_1–β_2	0.835***	0.7871***	0.8989***	0.8871***	0.4971***	0.8083***	0.7817***	0.7116***
	(1535.96)	(116.86)	(217.19)	(425.41)	(34.34)	(170.67)	(94.63)	(94.63)
R^2	0.8045	0.7446	0.8049	0.8752	0.7515	0.7788	0.7394	0.7002
				X = 0.60				
α	-0.0035***	-0.0034**	-0.0039***	-0.0028	0.0001	-0.0028**	-0.0047***	-0.0013
	(0.0005)	(0.0012)	(0.0010)	(0.0018)	(0.0015)	(0.0013)	(0.0015)	(0.0017)
β_1	1.0018***	0.9637***	1.0517***	1.0123***	0.9462***	0.9527***	1.0250***	0.9114***
	(0.0133)	(0.0448)	(0.0385)	(0.0272)	(0.0432)	(0.0382)	(0.0425)	(0.0501)
β_2	0.1912***	0.2066***	0.1218***	0.1466***	0.4512***	0.1518***	0.298***	0.2564***
	(0.0133)	(0.0438)	(0.0324)	(0.0287)	(0.0477)	(0.0358)	(0.0402)	(0.0423)
β_1–β_2	0.8107***	0.7571***	0.9299***	0.8658***	0.4949***	0.8008***	0.7270***	0.6550***
	(1399.59)	(100.60)	(234.23)	(375.27)	(39.94)	(165.67)	(71.18)	(71.18)
R^2	0.8143	0.7516	0.8200	0.8736	0.8082	0.7859	0.7962	0.6974
				X = 0.70				
α	-0.0030***	-0.0037***	-0.0045***	-0.0023	0.0006	-0.0026*	-0.0049***	-0.0011
	(0.0005)	(0.0012)	(0.0011)	(0.0021)	(0.0015)	(0.0015)	(0.0013)	(0.0018)
β_1	1.0082***	0.9871***	1.0921***	1.0108***	0.9508***	0.9490***	1.0853***	0.9167***
	(0.0140)	(0.0452)	(0.0407)	(0.0315)	(0.0419)	(0.0427)	(0.0372)	(0.0516)
β_2	0.2645***	0.2375***	0.1694***	0.2396***	0.5089***	0.2304***	0.3161***	0.3204***
	(0.0139)	(0.0442)	(0.0343)	(0.0333)	(0.0462)	(0.0400)	(0.0352)	(0.0436)
β_1–β_2	0.7437***	0.7496***	0.9227***	0.7713***	0.4419***	0.7187***	0.7692***	0.5964***
	(1070.27)	(97.03)	(206.68)	(221.16)	(33.94)	(106.88)	(55.66)	(55.66)
R^2	0.8118	0.7627	0.8222	0.8459	0.8281	0.7617	0.8510	0.7059

Table 3.6 displays the results of the CM test. Like the HM test, for every *X* threshold and during each time period, β is statistically significant. The statistically significant negative alphas mean the return on the market-timing portfolio is greater than that of the buy-and-hold portfolio, while the positive betas indicate a strong presence of market-timing ability in the probit model (a rejection of the null hypothesis β = 0).

Table 3.6. Cumby-Modest Test of the Probit Forecast Model

The table reports the value of the coefficients from the regression $R_{mt} - R_{ft} = \alpha + \beta Up_t + \varepsilon_t$, with standard errors reported in parentheses. Significance at the 10%, 5%, and 1% levels are marked by *, **, and *** respectively.

	1881-2020	**1881-1900**	**1901-1920**	**1921-1940**	**1941-1960**	**1961-1980**	**1981-2000**	**2001-2020**
N	1680	240	240	240	240	240	240	240
				X = 0.40				
α	-0.0192***	-0.0121***	-0.0171***	-0.0393***	-0.0114***	-0.0244***	-0.0127***	-0.0189***
	(0.0015)	(0.0023)	(0.0026)	(0.0067)	(0.0032)	(0.0033)	(0.0035)	(0.0041)
β	0.0469***	0.0328***	0.0395***	0.0878***	0.0403***	0.0493***	0.0376***	0.0414***
	(0.002)	(0.0035)	(0.0037)	(0.0091)	(0.0042)	(0.0045)	(0.0048)	(0.0052)
R^2	0.2393	0.2730	0.3221	0.2799	0.2772	0.3372	0.2043	0.2070
				X = 0.50				
α	-0.0236***	-0.0154***	-0.0218***	-0.0470***	-0.0117***	-0.0263***	-0.0173***	-0.0270***
	(0.0016)	(0.0026)	(0.0026)	(0.0071)	(0.0035)	(0.0034)	(0.0038)	(0.0043)
β	0.0491***	0.032***	0.043***	0.0915***	0.0376***	0.0502***	0.0407***	0.0491***
	(0.0021)	(0.0035)	(0.0036)	(0.0092)	(0.0044)	(0.0045)	(0.0049)	(0.0052)
R^2	0.2529	0.2621	0.3793	0.2933	0.2319	0.3437	0.2271	0.2683
				X = 0.60				
α	-0.0265***	-0.0167***	-0.0258***	-0.0528***	-0.0147***	-0.0286***	-0.0197***	-0.0271***
	(0.0017)	(0.0028)	(0.0029)	(0.0077)	(0.0038)	(0.0036)	(0.0043)	(0.0047)
β	0.0490***	0.0305***	0.0439***	0.0929***	0.0385***	0.0507***	0.0396***	0.0467***
	(0.0021)	(0.0036)	(0.0037)	(0.0095)	(0.0046)	(0.0046)	(0.0052)	(0.0056)
R^2	0.2370	0.2293	0.3714	0.2845	0.2249	0.3406	0.1944	0.2274
				X = 0.70				
α	-0.0289***	-0.0184***	-0.0276***	-0.0549***	-0.0170***	-0.0285***	-0.0280***	-0.0284***
	(0.0019)	(0.0031)	(0.0032)	(0.0085)	(0.0041)	(0.004)	(0.0049)	(0.005)
β	0.0490***	0.0305***	0.0433***	0.0897***	0.0395***	0.0475***	0.0466***	0.0464***
	(0.0023)	(0.0038)	(0.0039)	(0.0102)	(0.0048)	(0.0049)	(0.0056)	(0.0058)
R^2	0.2183	0.2133	0.3384	0.2464	0.2188	0.2842	0.2250	0.2084

3.6. Robustness

The literature on evaluating the performance of market-timing strategies is vast. Data-snooping bias is a real risk in developing a technical trading strategy, as noted by BLL, Bajgrowicz and Scaillet (2014), STW, and Lo and MacKinlay (1990), among others. To combat data-snooping, BLL and STW use bootstrapping, with STW applying White's Reality Check (White, 2000). Fang, Jacobsen, and Qin (2014) follow the suggestions of Fama (1991) and Lakonishok and Smidt (1988) of using new data. While newer S&P 500® data are not currently available, the methodology can be applied to other sources of data. We implement both bootstrapping and different data sources to evaluate the viability of the probit model.

3.6.1. Bootstrapping

In bootstrapping, we generate 1,000 simulated datasets derived from the monthly S&P data using random sampling with replacement. The technical analysis indicators are recreated, and the probit model is applied to each dataset. From these results, we evaluate the distribution properties of the average monthly return for the buy-and-hold investor and the probit-based market-timer at various levels of X. The distribution of monthly returns is displayed in Figure 9, while the properties are displayed in Table 7.

Figure 3.9. Bootstrap Results

This graph shows the distribution of the mean monthly returns for the buy-and-hold portfolio and four levels of *X* (40%, 50%, 60%, and 70%) for the market-timing portfolio. Bin size is 0.05%.

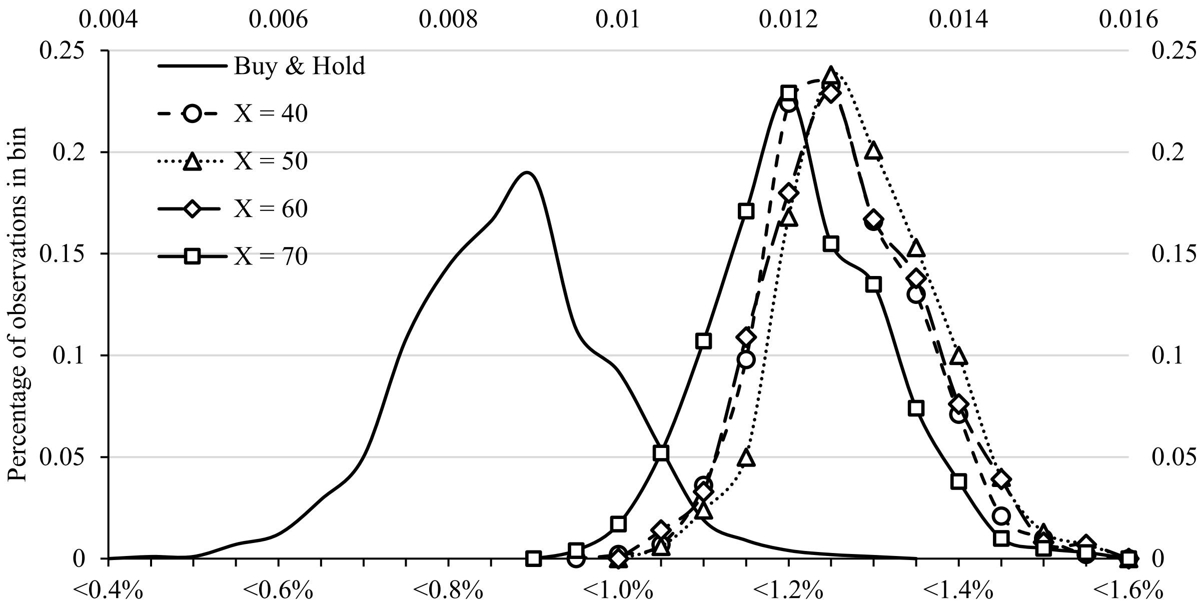


Table 3.7. Bootstrap Results

The table reports the results from using 1000 bootstrapped samples to test the market-timing probit model. Panel A displays the average of the summary statistics of the bootstrapped monthly return. Panel B displays the summary statistics of the average bootstrapped monthly return. Panel B displays the summary statistics of the bootstrapped Henriksson-Merton tests. Panel C displays the summary statistics of the bootstrapped Cumby-Modest tests.

A: Average of Summary Statistics of Bootstrapped Monthly Returns

This panel reports the average of the summary statistics of the monthly returns for the buy-and-hold portfolio and the market-timing portfolios. Each statistic is the average of that statistic for the 1000 bootstrapped samples.

Variable	B&H	X = 40	X = 50	X = 60	X = 70
N	1,000	1,000	1,000	1,000	1,000
Mean	0.8439%	1.2362%	1.2600%	1.2430%	1.1893%
Median	0.9420%	0.0000%	0.0115%	0.15022%	0.3374%
1st percentile	-12.4596%	-6.2119%	-7.4753%	-8.4526%	-9.2612%
99th percentile	11.9113%	10.8525%	11.0525%	11.2097%	11.3087%
Std. Dev.	0.0466	0.0307	0.0332	0.0355	0.0377
Skewness	0.1332	2.1287	1.6029	1.1781	0.8392
Kurtosis	12.0602	29.2350	25.2626	22.0509	19.4353

Table 3.7. Bootstrap Results (continued)

B: Summary Statistics of Bootstrapped Average Monthly Returns

This panel reports the summary statistics of the average monthly returns for the buy-and-hold portfolio and the market-timing portfolios. Standard deviations are multiplied by 1000 to eliminate leading zeros.

Variable	B&H	X = 40	X = 50	X = 60	X = 70
N	1,000	1,000	1,000	1,000	1,000
Mean	0.8439%	1.2362%	1.2600%	1.2430%	1.1893%
Median	0.8460%	1.2279%	1.2535%	1.2352%	1.1846%
1st percentile	0.5593%	1.0534%	1.0639%	1.0417%	0.9848%
99th percentile	1.1262%	1.4553%	1.4877%	1.4808%	1.4387%
Std. Dev. (× 1000)	1.1822	0.8509	0.8795	0.9206	0.9756
Skewness	0.0336	0.2864	0.2461	0.2784	0.2458
Kurtosis	3.3036	3.0484	3.0669	3.0097	3.1232

C: Henriksson-Merton Test of the Bootstrapped Data

This panel reports the value of the coefficients from the regression $R_{pt} - R_{ft} = \alpha + \beta_1 Up_t + \beta_2 Down_t + \varepsilon_t$, with bootstrap standard deviations (F-statistics for $\beta_1 - \beta_2$) reported in parentheses. Significance at the 10%, 5%, and 1% levels are marked by *, **, and *** respectively.

Variable	X = 40	X = 50	X = 60	X = 70
N	1000	1000	1000	1000
α	-0.0015	-0.0013	-0.0011	-0.0009
	(0.0017)	(0.0015)	(0.0014)	(0.0014)
β_1	0.7844***	0.8558***	0.9108***	0.9512***
	(0.0803)	(0.0687)	(0.0583)	(0.0495)
β_2	0.1794***	0.2546***	0.3401***	0.4347***
	(0.0520)	(0.0588)	(0.0661)	(0.0695)
$\beta_1 - \beta_2$	0.6050***	0.6012***	0.5707***	0.5165***
	(538.98)	(541.91)	(506.07)	(436.96)
R^2	0.6346	0.6935	0.7425	0.7847

Table 3.7. Bootstrap Results (continued)

D: Cumby-Modest Test of the Bootstrapped Data

This panel reports the value of the coefficients from the regression $R_{mt} - R_{ft} = \alpha + \beta Up_t + \varepsilon_t$, with bootstrap standard deviations reported in parentheses. Significance at the 10%, 5%, and 1% levels are marked by *, **, and *** respectively.

Variable	**X = 40**	**X = 50**	**X = 60**	**X = 70**
N	1000	1000	1000	1000
α	-0.0148*** (0.0017)	-0.0181*** (0.0018)	-0.0214*** (0.0019)	-0.0246*** (0.0021)
β	0.0392*** (0.0024)	0.0400*** (0.0024)	0.0408*** (0.0025)	0.0416*** (0.0027)
R^2	0.1757	0.1773	0.1717	0.1593

From Figure 3.9, it is clear the distributions of the monthly returns from the market-timing portfolios are higher than the buy-and-hold portfolios. Table 7, Panel A looks at the average of the summary statistics of the bootstrapped sample. The results are comparable to those in Table 3.3, and are similar in magnitude. Table 7, Panel B displays the summary statistics of the average monthly return of the bootstrapped sample, providing some of the details behind the distributions in Figure 3.9.

Panel C and Panel D show the average results of the HM and CM tests, respectively. Both tests confirm the capability of the market-timing probit model. In the HM test, the difference between β_1 and β_2 is positive and statistically significant. In the CM test, α is negative and statistically significant while β is positive and statistically significant.

3.6.2. Other sources of data

In addition to bootstrapping, we have conducted tests on several country indices, individual U.S. stocks, and Bitcoin. In all cases, the probit-based market-timing portfolios outperform the buy-and-hold portfolio, even with transaction costs. In some cases, that outperformance is large.

For example, \$1 invested in Bitcoin in 2011, when it was trading at just under \$1 per coin, was worth \$36,187 at the close of 2020. However, the market-timing portfolios, using daily data to make daily trading decisions, grew to between \$1.6 million and \$3.8 million, after transaction costs of 200 basis points (Bitcoin currently has a bid-ask spread of about 10 basis points).

3.7. Discussion and Conclusion

Investing strategies that outperform the broader stock market have been the subject of academic financial research for at least a century. In this paper, we use standard technical analysis indicators to develop a probit-based market-timing rule. Our probit model is robust to data-snooping bias and performs well in nearly every subperiod. The model is a simple yet powerful tool for investors to use to enhance their investing returns.

3.7.1. Possible Research Extensions

This paper used monthly returns to forecast market corrections one-month OOS. This forecast provides the market-timing, mean-variance investor an economically significant higher return than the buy-and-hold investor with, at most, monthly portfolio rebalancing. We also tested the model at the daily level on Bitcoin, but not other assets. If the model does work with higher frequency data on other assets, the economic value may not be significantly different from that of the monthly frequency, particularly after transaction costs. Even if the difference is significant, the mean-variance investors would need to weigh whether the difference is great enough to justify the time required to rebalance the portfolio more often. Either way, one potential extension of this paper is the use of higher frequency data in our model.

Addition, we only considered five of the most popular TA indicators in our research. There are many more indicators, not to mention Japanese candlestick patterns, western charting patterns, point-and-figure analysis, and others. Furthermore, on the indicators we used, we did not exhaust the ways in which technical analysts evaluate them. Similar probit models using new variables created from the indicators highlighted in this paper or from other indicators may provide even better results.

3.7.2. Taxes

Prior to this point in the paper, we have not discussed taxes. Undocumented results indicate that, depending on the marginal tax rate, taxes may completely eliminate the outperformance of the probit-based portfolios. However, for investors using the market-timing strategy proposed here inside tax-advantaged accounts such as 401(k)s and individual retirement accounts (IRA), switching between a money market account and a fee-free S&P index fund would be relatively seamless. Such a strategy could bolster the retirement accounts for millions of workers, leaving them much better prepared for retirement.

3.8.3. Other Considerations

The market-timing strategy proposed in this paper was evaluated from the perspective of a mean-variance, long-only investor. However, it is quite possible for other types of investors to use our probit model to enhance their returns. While mutual funds cannot be shorted, the advent of exchange traded funds (ETF) allows investors to short the market during forecasted correction periods instead of simply moving into cash. Or, instead of shorting, investors could choose to go long in a reverse fund. Additionally, there is the possibility of using leveraged ETFs to further increase investment returns.

Likewise, investors could consider using listed options as part of their investment strategy. Instead of selling the index fund and switching into cash, investors could sell SPX call options against their position in the index fund or buy SPX put options as insurance. Yet another research extension of this paper could be on the behavior of options around changes in the forecasted probability of correction.

3.8.4. Final Remarks

Regardless of which type of investor is using the probit market-timing model developed in this paper, our OOS tests support the feasibility of forecasting a down month in the stock market one month in advance. In the overall sample period and each subperiod, the result was strongest when the *X* threshold was set to 50%. At the 50% threshold level, from 1881 to 2020, the average annual compound rate of return of our probit market-timing strategy was over 12%, compared to 9.19% for the buy-and-hold strategy. This difference is both statistically and economically significant. Tests of model performance and robustness checks confirm the statistically significant market-timing ability of the strategy.

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Appendix: Variables from Technical Analysis Indicators

This table describes the variables used in the probit model and how they are calculated.

Variable	Description	Calculation
Moving Averages (MA)		
SPMA_3	Level of the standardized 3-period (month) moving average	The *PMA_3* is the sum of this month's (or period) closing price (or index level) and the closing price of the previous two months all divided by three. This is standardized by dividing it by this month's closing price.
SPMA_9	Level of the standardized 9-period (month) moving average	The *PMA_9* is the sum of this month's (or period) closing price (or index level) and the closing price of the previous eight months all divided by nine. This is standardized by dividing it by this month's closing price.
Δ_*SMA*	The change in the difference between the short and long MAs from t–1 to t	*MA_histogram* is the difference between the *PMA_3* and *PMA_9*. This is standardized by dividing it by this month's closing price. Δ_*SMA* is then calculated as this month's *SMA_histogram* minus last month's *SMA_histogram*.
roc_SMA	The rate of change in the difference between the short and long MAs from t–1 to t	The difference between this month's Δ_*SMA* and last month's Δ_*SMA*.
SMACI	Indicator variable for the difference between the short and long MAs	Equal to 1 when *MA_histogram* is negative, 0 otherwise.
*SMACI*_Δ	Indicator variable for Δ_MA	Equal to 1 when Δ_*SMA* is negative, 0 otherwise.
SMACI_roc	Indicator variable for roc_MA	Equal to 1 when *roc_SMA* is negative, 0 otherwise.
Bollinger Bands (BB)		
SMBB	Level of the standardized Middle Bollinger Band	The *MBB* is the sum of this month's (or period) closing price (or index level) and the closing price of the previous nineteen months all divided by twenty. This is standardized by dividing it by this month's closing price.
STBB	Level of the standardized Top Bollinger Band	The *TBB* is the equal to the *MBB* plus two standard deviations of the past twenty closing prices. This is standardized by dividing it by this month's closing price.
Δ_*SMBB*	The change in the level of the standardized Middle Bollinger Band from t–1 to t	The difference between this month's *MBB* and last month's *MBB*.
Δ_*STBB*	The change in the level of the standardized Top Bollinger Band from t–1 to t	The difference between this month's *TBB* and last month's *TBB*.
roc_SMBB	The rate of change in the level of the standardized Middle Bollinger Band from t–1 to t	The difference between this month's Δ_*SMBB* and last month's Δ_*SMBB*.
roc_STBB	The rate of change in the level of the standardized Top Bollinger Band from t–1 to t	The difference between this month's Δ_*TMBB* and last month's Δ_*TMBB*.
*SMBB*_Δ_*i*	Indicator variable for Δ_SMBB	Equal to 1 when Δ_*SMBB* is negative, 0 otherwise.
*STBB*_Δ_*i*	Indicator variable for Δ_STBB	Equal to 1 when Δ_*TMBB* is negative, 0 otherwise.
*SLBB*_Δ_*i*	Indicator variable for Δ_SBBB	Equal to 1 when Δ_*LMBB* is negative, 0 otherwise.
SMBB_roc_i	Indicator variable for roc_SMBB	Equal to 1 when *roc_SMBB* is negative, 0 otherwise.
STBB_roc_i	Indicator variable for roc_STBB	Equal to 1 when *roc_TMBB* is negative, 0 otherwise.
SLBB_roc_i	Indicator variable for roc_SBBB	Equal to 1 when *roc_LMBB* is negative, 0 otherwise.

Variable	Description	Calculation
Moving Average Convergence / Divergence (MACD)		
SMACD	Level of the standardized MACD	The *MACD* is the difference between a 12-period *EMA* and 26-period EMA. The EMA is calculated as [*Close* – EMA(previous period)] × *Multiplier* + EMA(previous period), where the *Multiplier* = 2 / (*n* + 1). The *MACD* is standardized by dividing it by this month's closing price.
SMACD_sig	Level of the standardized MACD_sig	The *MACD_sig* is the 3-period EMA of the *MACD*. This is standardized by dividing it by this month's closing price.
Δ_*SMACD*	The change in the difference SMACD and the SMACD_sig from t–1 to t	*MACD_histogram* is the difference between the *MACD* and *MACD_sig*. This is standardized by dividing it by this month's closing price. Δ_*SMACD* is then calculated as this month's *SMACD_histogram* minus last month's *SMACD_histogram*.
roc_SMACD	The rate of change in the difference SMACD and the SMACD_sig from t–1 to t	The difference between this month's Δ_*SMACD* and last month's Δ_*SMACD*.
SMACD_i	Indicator variable for the difference between the SMACD and the SMACD_sig	Equal to 1 when *SMACD_histogram* is negative, 0 otherwise.
*SMACD_*Δ*_i*	Indicator variable for Δ_SMACD	Equal to 1 when Δ_*SMACD* is negative, 0 otherwise.
SMACD_roc_i	Indicator variable for roc_SMACD	Equal to 1 when *roc_SMACD* is negative, 0 otherwise.
Relative Strength Index (RSI)		
RSI	Level of the RSI	The *RSI* is calculated as 100 - [100 / (1 + *RS*)], where *RS* = (Average Gain) / (Average Loss). For more details see Wilder (1978).
Δ_*RSI*	The change in the level of the RSI from t–1 to t	The difference between this month's *RSI* and last month's *RSI*.
roc_RSI	The rate of change in the level of the RSI from t–1 to t	The difference between this month's Δ_*RSI* and last month's Δ_*RSI*.
RSI_i	Indicator variable for RSI overbought and oversold levels	Equal to 1 when *RSI* is oversold (below 30), 2 when *RSI* is overbought (above 70), and 0 otherwise
*RSI_*Δ*_i*	Indicator variable for Δ_RSI	Equal to 1 when Δ_*RSI* is negative, 0 otherwise.
RSI_roc_i	Indicator variable for roc_RSI	Equal to 1 when *roc_RSI* is negative, 0 otherwise.
Stochastic Oscillator (STO)		
STO_K	Level of the STO %K line	Calculated as (*Close* – *Low14*) / (*High14* – *Low14*) × 100, where *Close* is this month's closing price, *Low14* is the lowest price in the past 14 months and *High14* is the highest price in the past 14 months
STO_D	Level of the STO %D line	A 3-period SMA of *STO_K*
Δ_*STO*	The change in the difference %K and %D from t–1 to t	*STO_histogram* is the difference between the *STO_K* and *STO_D*. Δ_*STO* is then calculated as this month's *STO_histogram* minus last month's *STO_histogram*.
roc_STO	The rate of change in the difference %K and %D from t–1 to t	The difference between this month's Δ_*STO* and last month's Δ_*STO*.
STO_K_i	Indicator variable for %K overbought and oversold levels	Equal to 1 when *STO_K* is oversold (below 20), 2 when *STO_K* is overbought (above 80), and 0 otherwise
STO_D_i	Indicator variable for %D overbought and oversold levels	Equal to 1 when *STO_D* is oversold (below 20), 2 when *STO_D* is overbought (above 80), and 0 otherwise

Variable	Description	Calculation
STO_i	Indicator variable for the difference between %K and %D	Equal to 1 when *STO_histogram* is negative, 0 otherwise.
STO_d_i	Indicator variable for Δ_STO	Equal to 1 when Δ_*STO* is negative, 0 otherwise.
STO_roc_i	Indicator variable for roc_STO	Equal to 1 when *roc_STO* is negative, 0 otherwise.