Three Papers in Applied Macroeconomics

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THREE PAPERS IN APPLIED MACROECONOMICS

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Economics

by
Jeremy W. Choquette
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Accepted by:
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Dr. Robert F. Tamura
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Dr. Scott L. Baier
Abstract

The first chapter of this dissertation addresses the impacts of monetary policy shocks on bank lending behavior in the United States and the role recessions play through a risk taking transmission mechanism. I employ a vector autoregression (VAR) identified with sign and zero restrictions to simulate a monetary policy shock implemented by the Federal Reserve consistent with the economic theory suggesting unconventional monetary policy measures. I find that banks respond to expansionary monetary policy shocks by taking additional risk through lowering lending standards, however banks still experience a compression in lending margins, indicating little success in their efforts to stabilize reductions in profits. I also include a number of counterfactual interest rates to allow Fed policy rates to reflect negative interest rate policies to compare monetary policy shocks across the conventional and unconventional monetary policy regimes in a consistent manner. I find that banks take less risk in the unconventional monetary policy regime relative to the conventional regime, however they experience a larger reduction in lending margins relative to the pre-Financial Crisis period. Use of a forecast error variance decomposition indicates the risk channel played a larger role in the post-Financial Crisis period, carrying implications for Fed policy in considering this particular transmission mechanism in unconventional monetary policy measures.

The second chapter of this dissertation addresses the foreign central bank
responses of 12 advanced economies and 12 emerging market economies to United States unconventional monetary policy shocks identified by a combination of sign and zero restrictions in a global vector autoregression (GVAR) framework. I find foreign central banks follow in kind with United States unconventional monetary policy measures, such as Quantitative Easing, in order to offset undesirable spillover effects. My results also indicate that United States Quantitative Easing plays a more substantial role in determining monetary easing conditions in emerging markets than in advanced economies. Additionally, I find foreign central banks with inflation targeting or floating exchange rate policies tend to follow a United States Quantitative Easing shock with more stable monetary policy responses, with larger increases in output than non-inflation targeting or managed exchange rate regimes. My results are robust to various changes in the specifications and identifying restrictions.

The third chapter was written with Dr. Robert F. Tamura. We introduce a novel data set to empirically test a dynamic, dynastic human capital model developed by Tamura, Simon, and Murphy (2016), yielding predictions of the relative efficiency of school for black and white students during the Jim Crow era. By providing measures developed within the data set, we can test the parametrizations of key variables with respect to access to education calibrated within the model. Our results suggest that the model accurately describes the key educational values generated by the model, and confirms the results of the theoretical framework developed by Tamura, Simon, and Murphy (2016) in that blacks faced substantially higher marginal costs of education relative to whites as a result of the lack of equal per-pupil expenditures allocated at the state level during segregation, lower levels of human capital accumulation of African American parents relative to white parents, and the disparity of income across both races. This paper contributes to the literature by presenting a novel data set regarding expenditures per pupil for white and African American
students for the years 1890-1960, and also confirming the fit of the model developed by Tamura, Simon, and Murphy (2016).
Dedication

I would first like to thank all of my parents: my mother, Joanne Callahan, my father, Mitchell Choquette, my stepfather, Brian Callahan, my stepmother, Tracey Choquette, and of course, my “third” dad, Richard Thetford. You all believed in me before anyone else ever did. My biological parents brought me into this world, and were ALWAYS on my side, and for each night you stayed up with me while I was struggling through the hardest parts of my life (and my first year in graduate school), thank you. I will always love you for working to make me who I am today. And to my step-parents, you came into my life, and had no obligation to love me, but chose to anyways. Whether it was being there for me when I had to put my cat to sleep, or travelling alone through Berlin at 3:00 AM to find something to help me recover from food poisoning, you both went above and beyond what ANYONE would expect, and you showed me that family isn’t about blood; it’s about love. Parents don’t need to be biological to be parents. And of course, to my “third” dad, Richard Thetford, you took me in as a surrogate son, and from raising me to my third degree in the Masonic Lodge to being there with Brian and me during one of the toughest times in my life, you have proven that loyalty is a rare thing, and it’s never to be taken for granted.

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South Carolina Log Per Pupil Expenditures (Nominal) ......................................................... 207
Tennessee Log Per Pupil Expenditures (Nominal) ............................................................... 208
Texas Log Per Pupil Expenditures (Nominal) ...................................................................... 208
Virginia Log Per Pupil Expenditures (Nominal) ................................................................. 209
Alabama Log Earnings (Nominal) ......................................................................................... 210
Arkansas Log Earnings (Nominal) ......................................................................................... 210
Delaware Log Earnings (Nominal) ......................................................................................... 211
Florida Log Earnings (Nominal) ........................................................................................... 211
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Louisiana Log Earnings (Nominal) ......................................................................................... 212
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Mississippi Log Earnings (Nominal) ....................................................................................... 213
North Carolina Log Earnings (Nominal) .............................................................................. 214
South Carolina Log Earnings (Nominal) .............................................................................. 214
Tennessee Log Earnings (Nominal) ......................................................................................... 215
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168  Tennessee Log Kappa Tau ........................................ 222
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173  Delaware Log Kappa ............................................... 225
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177  Maryland Log Kappa ............................................. 227
178  Mississippi Log Kappa .......................................... 227
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180  South Carolina Log Kappa ...................................... 228
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183  Virginia Log Kappa .............................................. 230
Chapter 1

Bank Lending and the Risk Channel of Monetary Policy

1.1 Introduction

Low interest rates maintained by the Federal Reserve after the Financial Crisis of 2007/2008 led to the adoption of unconventional monetary policy measures. When the Federal Funds market was rendered inert by the zero lower bound (ZLB) for nominal interest rates, the Federal Reserve altered its policy regime by targeting longer term interest rates and engaging in Large Scale Asset Purchase programs (LSAPs). Between November 2008 and October 2014, the Federal Reserve implemented three rounds of Quantitative Easing, purchasing $4.2 trillion in Treasury and mortgage backed securities to stimulate economic recovery. Figure 1.1 presents the balance sheet trends of the Federal Reserve between 2008 and 2018.

As risk taking by financial institutions is considered a factor behind the onset of the Financial Crisis, analyzing the effects of monetary expansion on this behavior is of key interest in understanding the implications of monetary policy. As discussed by Hancock (1985) and Aharony et al. (1986), a changing interest rate environment can influence banks’ perceptions of risk, in that lower short term interest rates are
related to a reduction in commercial bank profitability. During recessions in the business cycle, Acharya et al. (2012) and Beck et al. (2006) show that competition for liquidity and customers can narrow banks’ lending margins and incentivize more risk taking.

Coined the “risk-taking channel of monetary policy” by Borio and Zhu (2012), the impact of monetary policy on the willingness of market participants to assume additional exposure to risk influences financial conditions and ultimately transmits to increases in aggregate output. There are numerous effects of this channel. The first effect operates through the basis of valuations, income, and cash flows. Low interest rates and sizable excess reserves held by financial institutions alter banks’ risk perceptions through increases in the value of real and financial collateral. The increases in production and incomes lead to a higher tolerance of risk among borrowers. The second effect ensues when monetary policy shocks impact bank profitability. When bank profits are threatened and borrowers are more willing to take additional risk, banks may engage in riskier loans to maintain their profit margins.
Rajan (2006) and Buch, Eickmeier, and Prieto (2014) discuss conditions where negative deviations from nominal rate of return targets can induce banks to seek higher yields to maintain the trust of their investors. As monetary policy shocks transmit through the economy, a “search for yield” (Rajan, 2006) can affect risk taking. This search is induced when financial institutions receive lower yields on their short-term assets relative to long-term liabilities. Thus, banks may alter their holdings in favor of riskier assets in hopes of garnering higher rates of return. Dell’Ariccia, Leaven, and Marquez (2014) find affected banks face an adverse selection problem in assessing borrowers, while macroprudential policies can lead to a credit boom and lower bank lending standards. As interest rates decline, Maudos and deGuevara (2004) suggest the increase in banking sector competition can lead to reductions in lending margins, thereby threatening bank profitability.

The theoretical dynamic stochastic general equilibrium (DSGE) literature addresses this channel of monetary policy, with de Groot’s (2014) model implying banks reduce reliance on debt finance and decrease leverage in response to expansionary monetary policy shocks. Dell’Ariccia, Laeven, and Marquez (2014) develop a DSGE that establishes a link between risk-taking behavior and banks’ capital structures. The empirical literature from Altunbas, Gambacorta, and Marques-Ibanez (2014), Buch, Eickmeier, and Prieto (2014), Dell’Ariccia, Laeven, and Suarez (2017) suggest that small and modestly capitalized banks may be more likely to take risk, which can be explained by a lower demand for loans in the banking sector and an inability to adjust capital structures. Abbate and Thaler’s (2015) DSGE suggests that monetary authorities can benefit by stabilizing real interest rates, trading off more inflation volatility in exchange for less volatility in risk taking and output.

Asset purchases may have different effects as perceptions of risk are mitigated during various monetary policy regimes. Gertler and Kerati (2011) find that, at the
ZLB, policies such as central bank credit intermediation can increase production and inflation, while decreasing interest rate spreads. Meier (2009) has similar findings for the United Kingdom. Hamilton and Wu (2012) and Stroebel and Taylor (2009) suggest monetary expansion in the form of LSAPs reduce yield spreads. Baumeister and Benati (2012) find that asset purchase programs in the U.S. and the U.K. assisted in preventing risks of both deflation and output collapses. These findings are confirmed by Wieladek and Weale (2016), who employ vector autoregressions (VARs) to identify a monetary policy shock in the United States and United Kingdom. Schenkelberg and Watzka (2013) use a similar approach in Japan and also find that LSAPs had expansionary effects. Wieladek and Weale (2016) identify the existence of the risk channel of monetary policy operating through perceptions of uncertainty, measured by the Chicago Board Options Exchange index of implied volatility of the S&P 500 (CBOE VIX) and household uncertainty surveys. While they identify this channel in the United States, they do not address the impact of risk through bank lending behavior.

The responses to monetary expansion via changes in risk-taking can be driven via a number of economic and financial indicators. Bekaert et al. (2013) find a close relationship between the policy rate chosen by the Fed and measured risks, in which monetary easing conditions lead to reductions in the CBOE VIX. Bloom (2009) argues the VIX is a reflection of market uncertainty, while Adrian and Shin (2010), Bruno and Shin (2015), and Miranda-Agrippino and Rey (2013) argue the VIX is a reflection of investors’ risk appetites. Weale and Wieladek’s (2016) VARs include the VIX, household survey measures of uncertainty, interest rate futures, and BBB-AAA corporate bond spreads. They find that the risk channel of monetary policy played a non-trivial role in the real economic responses to Quantitative Easing in the United States. Finally, Neuenkirch and Nockel (2018) argue the expansionary effects can be
driven through changes in bank lending as a result of increased liquidity, where they measure risk by the percentage of banks reporting a tightening in credit conditions.\textsuperscript{1}

As central banks have adopted more accommodative monetary policy, the empirical evidence suggests that the zero lower bound has been less binding than previously considered, and that the effective lower bound may well be below zero (Jobst and Lin; 2016). Negative interest rate policies adopted in the Euro Area have been argued to contribute to a modest expansion in financial conditions, however there is evidence to suggest such policies affect bank profitability (Jobst and Lin; 2016, and Carbo-Valverde, Cuadros-Solas, and Rodriguez-Fernandez; 2019). Carbo-Valverde, Cuadros-Solas, and Rodriguez-Fernandez (2019) argue that negative interest rate policies in the European banking sector have a substantially negative impact on banks’ net interest margins, compared to European economies that do not adopt negative policy rates. Basten and Mariathasan (2018) discuss how negative interest rates substantially increase bank operating costs, while portfolio rebalance effects lead to more lending, and risk-taking reduces capital cushions and liquidity conditions. Demri-lap, Eisenschmidt, and Vlassopoulos (2017) find that negative interest rate policies adopted by the European Central Bank lead to banks extending more loans while holding non-domestic government bonds.\textsuperscript{2}

This paper contributes to the literature in a number of important ways. First, while a majority of the existing literature on the risk channel of monetary policy uses bank-level data to explore the relationship between monetary conditions and risk-taking behavior via panel data methods, I investigate the macroeconomic implications of this particular channel, similar to Neuenkirch and Nockel (2018). To achieve this, I

\textsuperscript{1}Neuenkirch and Nockel (2018) implement a VAR methodology with bank lending standards as their variable to account for bank risk-taking.

\textsuperscript{2}As the Federal Reserve has stated on multiple occasions that they have no intention of adopting negative interest rate policies, empirical studies to address the impact of negative interest rate policies only exist for foreign economies.
employ a vector autoregression with Bayesian methods to identify shocks that isolate the effect of this particular transmission mechanism in which reductions in bank profitability may induce banks to take more risk. My results indicate that banks take additional risk in response to monetary policy shocks, however they do not successfully prevent a compression in lending margins.

Second, I am expanding upon the work of Neuenkirch and Nockel (2018) to the United States. In order to more accurately reflect the financial and monetary conditions of the United States, I alter the specification used by Neuenkirch and Nockel (2018) to align with policy implemented by the Federal Reserve. I use a combination of sign and zero restrictions to identify an exogenous one standard deviation increase in reserve balances as the shock of interest, with results carrying policy implications regarding the Federal Reserve’s dual mandate, which is to promote maximum employment and stable prices with a 2% annualized rate of inflation.

Third, I employ a number of counterfactual interest rates to develop a consistent method in which I can compare banking sector responses to monetary policy shocks via the risk channel across the pre- and post-Financial Crisis regimes. When scaling the impulse responses to be consistent with a 25 basis point cut in the Fed policy rate across both regimes, my findings suggest that banks take less risk in the post-Financial Crisis period, however they also experience a larger compression in lending margins relative to before the onset of the Financial Crisis. These results are consistent with the findings of Jobst and Lin (2016), Carbo-Valverde, Cuadros-Solas, and Rodriguez-Fernandez (2019), and Demrilap, Eisenschmidt, and Vlassopoulos (2017), who address the impact of negative interest rate policies in the Euro area and the role that the impact on operating costs faced by financial institutions may...
play in increased risk-taking in the aggregate economy.

Fourth, I employ a forecast error variance decomposition (FEVD) to assess the contribution of monetary shocks across both regimes, finding that monetary policy shocks explain more of the variance in the banking sector variables in the unconventional regime. This provides evidence that the risk channel of monetary policy played a larger role after the Financial Crisis than before, lending to additional implications for Fed policy to consider the role of this transmission mechanism in setting future policy measures.

The rest of this paper is as follows: Section 1.2 presents the empirical strategy to identify a monetary policy shock while constrained at the ZLB, Section 2.3 presents the results regarding the risk channel of monetary policy to provide insight into the banking sector responses to innovations consistent with the policy tools used by the Federal Reserve in response to the Financial Crisis of 2007/08, Section 1.4 explores numerous counterfactual analyses in which I construct a number of Taylor Rule Specifications and employ a Shadow Federal Funds rate to assess the implications regarding the Federal Reserve allowing negative interest rates in their policy measures and the impact it has across risky lending behavior across the two different monetary policy regimes. I also employ an FEVD to assess the magnitude of the role the risk channel played in each regime, and finally, Section 3.6 concludes.
1.2 Empirically Assessing the Risk Channel of Monetary Policy

1.2.1 VAR Estimation

To assess the role the risk channel plays in bank lending behavior, I estimate a VAR for the period Q4:2008-Q4:2018 with quarterly data, which encompasses the period during which the Federal Reserve Bank was constrained by the ZLB for short term nominal rates and resorted to unconventional monetary policy measures such as QE and Operation Twist. While Quantitative Easing culminated in October 2014, and the Federal Reserve raised the Federal Funds Rate for the first time since 2008 in 2015, the Federal Open Market Committee has not unwound the Fed’s balance sheet to a sufficient level to allow for the Fed Funds Rate to operate as the main operating tool for policy.

I estimate the following reduced form VAR with a deterministic trend

\[ y_t' = c' + \sum_{\ell=1}^{p} y_{t-\ell}' A_{t} + t' \gamma + u_t', \]

where \( y_t \) is a vector of endogenous variables including US data for the log of real GDP, the log of the core PCE Price Index\(^4\), the log of reserve balances held by depository institutions at the Federal Reserve, Interest on Excess Reserves (serving as the Fed’s policy rate), the 10 Year Treasury yield (to capture the term structure of interest rates)\(^5\), lending standards, and bank lending margins. Bank lending standards are

\(^4\)The use of core PCE, excluding energy and food, precludes exogenous price movements stemming from these two sources, allowing me to establish a parsimonious model without an exogenous oil price indicator.

\(^5\)Schenkelberg and Watzka (2013) and Weale and Wieladek (2016) suggest the use of the 10 year government bond yield to reflect the term structure of interest rates during an unconventional monetary policy regime. As a goal of the Federal Reserve during Quantitative Easing was to flatten the yield curve, the use of the variable in the VAR specification is appropriate.
expressed as the net percentage of banks reporting a tightening in lending standards and is the risk indicator in my estimations. Increases in this variable indicate more banks are reporting tightening in credit conditions. Thus, in response to monetary policy shocks with a reduction in policy rates, banks may face an inability to maintain their profit margins and are thus induced to acquire riskier assets in their “search for yield”.

Finally, lending margins are the difference between interest rates on new business loans and a weighted average interest rate on new deposits from households and non-financial corporations. Neuenkirch and Nockel (2018) include this in their VAR as a measure of bank profitability. During recessions in which monetary policy shocks are present, lending margins face a significant compression, thereby threatening commercial bank profitability. Figure 1.2 presents lending standards and margins over the period of Q2:1990-Q4:2018, with the shaded areas representing recessions as defined by the National Bureau of Economic Research (NBER). The data show a clear relationship regarding increases in lending standards during recessions in which bank demand for liquidity increases and lending begins to tighten. Additionally, while lending margins have followed a downward trend over the sample period, there is a noticeable compression during a recession, in which bank profitability through lending is reduced.

I estimate the VAR with a lag length of 2, as determined by a majority vote of the Akaike Information Criterion (AIC), the Bayes-Schwartz Information Criterion (BIC), and the Hannan-Quinn Information Criterion (HQ). All data in this specification are acquired from the Federal Reserve Economic Database (FRED).
1.2.1.1 VAR Identification

The challenge in VAR estimation is to disentangle the orthogonal structural shocks from the correlated, reduced-form residuals. Traditional VAR methodology implements a recursive ordering as an identification scheme, however issues arise in justifying the ordering of the variables.\(^6\) A recursive ordering also imposes exclusion restrictions, which do not naturally arise in DSGE models. An alternative identification scheme is based on the work of Uhlig (20015), Schenkelberg and Watzka (2013), Wieladek and Weale (2016), and Neuenkirch and Nockel (2018) and impose sign restrictions on the reduced form impulse responses.

From Equation 1.1 (suppressing the trend term), I can recover the structural form VAR

\[
y'_t A_0 = c^* + \sum_{\ell=1}^p y'_{t-\ell} A^*_\ell + u^*_t, \tag{1.2}
\]

where \(A_0\), is the matrix of contemporaneous autoregressive coefficients, \(c^* = c'A_0\), the matrix \(A^*_\ell\) is composed of the structural autoregressive coefficients related to the reduced form parameters via

\(^6\)The ordering of the variables is typically from slowest to fastest moving variables.
\[ A_t^* = A_t A_0, \]  
(1.3)

the structural residuals are related to the reduced form residuals

\[ u_t^* = u_t A_0, \]  
(1.4)

and the reduced form residual variance/covariance matrix is given by

\[ E[u_t u_t'] = \Sigma = (A_0 A_0')^{-1}. \]  
(1.5)

\( A_0 A_\ell \) is the matrix of lagged structural autoregressive coefficients, and the reduced form residuals are related to the structural errors by \( u_t^* = u_t' A_0 \).

Identification of \( A_0 \) can either be done by directly imposing restrictions such that \( u_t^* A_0^{-1} = u_t' \), or by inferring restrictions on \( A_0^{-1} \) by sign restrictions placed on the impulse responses, as utilized by Uhlig (2005), Mountford and Uhlig (2009), and Arias, Rubio-Ramirez, Waggoner, and Zha (2018).

The Bayesian approach to identification with sign restrictions uses a weakly informative inverted Normal-Wishart prior on the estimated variance/covariance matrix and avoids priors set too tightly to impose bias on the posterior parameters, and the sign restrictions can persist for \( k \) periods, where \( k \geq 1 \). Direct imposition of the sign restrictions generates a posterior via a Markov Chain Monte Carlo (MCMC) sampling method and extracts the orthogonal innovations of the VAR using a lower-triangular Cholesky decomposition of \( \Sigma \) to find \( A_0 \) based on prior beliefs about the signs of the impact of a particular shock.\(^7\) There are multiple advantages to the use of sign identification. Sign restriction identification does not contain exclusion

\(^7\)The Cholesky decomposition serves only as a method of orthogonalization and is not used to identify shocks.
restrictions and allows for the contemporaneous transmission between multiple variables that do not exist in a recursive ordering. It should be of note, however, that this identification method relaxes the exclusion restrictions on the recursively identified model, implying that previously unrestricted parameters in $A_0^{-1}$ are restricted instead, and thus the recursive model is not nested within the sign-identified model. Therefore, the two approaches to identification represent alternatives to one another, and it is not possible to validate or invalidate implications of a recursively identified VAR with a sign-identified VAR model.

As I am interested in only one particular shock, I identify elements in one column of $A_0^{-1}$. This represents the responses of the model’s corresponding variables to a monetary policy shock via an one standard deviation increase in the Reserve Balances equation in the VAR.\textsuperscript{8} A random impulse vector $\alpha$ is drawn from the unit sphere, and is multiplied by the impulse responses computed from the Cholesky decomposition of the residuals. If the structural impulse responses match the imposed sign restrictions, the draw is kept. If not, the draw is discarded and the process repeats until the number of accepted draws or maximum iterations is reached.

1.2.2 Identifying Restrictions

As the Federal Reserve’s policy tool changed from the Federal Funds Rate to the quantity of excess reserves held by depository institutions at the Federal Reserve, I identify an unconventional monetary policy shock by imposing an innovation to the reserve balance equation. I place positive sign restrictions on reserve balances,\textsuperscript{8}The Fed’s change in policy tools from the Federal Funds Rate to the level of excess reserve balances held by depository institutions at the Federal Reserve Bank necessitates an alternative identification scheme relative to the conventional monetary policy regime in which identification is performed by imposing a shock to the policy rate equation. This unconventional monetary policy identification strategy is similar to the scheme employed by Schenkelberg and Watzka (2013) and Weale and Wieladek (2016).
the price level, and GDP. In the presence of financial frictions such as the imperfect substitutability between short and long term bonds or a preferred risk habitat for investors suggested by Vayanos and Vila (2009), economic theory suggests that LSAPs will lead to a reduction in long term government bonds by reducing term premia (portfolio rebalancing effects). Even in the absence of LSAP shocks, announcements of asset purchases can signal that the policy rate will remain low for longer than previously expected, and also reduce the long term rate (signaling effects). While Weale and Wieladek (2016) discuss that one of these two channels can operate (but not both simultaneously), the risk channel can operate in tandem with either. In addition to the reduction on the Fed policy rate, I also place a negative sign restriction on the 10 year Treasury Yield. The specifications and identification schemes are similar to that of Schenkelberg and Watzka (2013) and Wieladek and Weale (2016), who impose positive sign restrictions to the base monetary aggregate equation in the VAR to simulate an unconventional monetary policy shock.⁹

A problem within the sign identified VAR literature is that sign restrictions do not rule out the existence of other orthogonal innovations with the same pattern as the shock of interest; each draw can be extracted from a different underlying structural model. According to Fry and Pagan (2011) the “multiple models problem” can imply ambiguity in proper identification of the shock of interest. Therefore, Fry and Pagan (2011), Schenkelberg and Watzka (2013), and Weale and Wieladek (2016) discuss the benefits of imposing additional sign restrictions to further ensure proper identification of shocks as a means to address the multiple models problem.

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⁹Additional sign restrictions on other variables are supported by Schenkelberg and Watzka (2013), Weale and Wieladek (2016), and Neuenkirch and Nockel (2018). Schenkelberg and Watzka (2013), Weale and Wieladek (2016), and Neuenkirch and Nockel (2018) impose positive sign restrictions on consumer prices and negative sign restrictions on the interest rate variables. Neuenkirch and Nockel (2018) also impose a positive sign restriction on real GDP. The results of Weale and Wieladek (2016) suggest a positive response in real GDP, further justifying the imposition of this additional restriction in the identification scheme.
### Table 1.1: Sign Identifying Restrictions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Log GDP</th>
<th>Log PCE</th>
<th>Log Core Balances</th>
<th>Log Reserve Balances</th>
<th>Interest on 10 Year Lending</th>
<th>Lending Standards</th>
<th>Lending Margin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate Demand Shock</td>
<td>+ + +</td>
<td>0</td>
<td>+</td>
<td>- -</td>
<td>+</td>
<td>+</td>
<td>- -</td>
</tr>
<tr>
<td>Aggregate Supply Shock</td>
<td>+ -</td>
<td>0</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Monetary Policy Shock</td>
<td>0 0</td>
<td>+ +</td>
<td>+</td>
<td>- -</td>
<td>+</td>
<td>+</td>
<td>- -</td>
</tr>
</tbody>
</table>

Note: The table shows the sign and zero restrictions on the endogenous variables applied to identify a monetary policy shock and separate them from other business cycle shocks.

identification scheme used in the monetary policy shock makes use of additional sign restrictions (positive restrictions on prices and GDP), and only the banking sector variables remain unrestricted. The identifying restrictions are included in in Table 2.2. In addition, to overcome the multiple models problem discussed by Fry and Pagan (2011), I provide the identifying restrictions for demand and supply shocks, as done by Schenkelberg and Watzka (2013) and Weale and Wieladek (2016). Weale and Wieladek (2016) argue that in the presence of a demand shock, increases in prices and output will also lead to a non-negative response in the long term bond yields. Under a supply shock, output and prices will move in opposite directions and the long term Treasury yield will be reduced. For the results of the MCMC sampling process, I present the median impulse response draw and the 68% Bayesian credibility bands from 10,000 accepted draws.
1.3 Results

This section presents the results from the VAR estimation. Subsection 1.3.1 presents the impulse responses for the unconventional monetary policy regime, which are scaled to a one standard deviation increase in the log of reserve balances held by depository institutions at the Federal Reserve. Subsection 1.3.2 presents the impulse responses for the conventional monetary policy regime, in which the impulse responses are scaled to a one standard deviation reduction in the Federal Funds Rate. Subsection 1.4 presents a number of alternative interest rates for the unconventional monetary policy regime that serve as counterfactuals for the Fed’s policy rate, thereby allowing for comparison of the responses of banking sector variables in a consistent manner. Finally, to investigate the role the risk channel played in each monetary policy regime, Subsection 1.4.2 presents the FEVD plots regarding the contribution of an asset purchase shock to the variables included in the VAR across both regimes.

1.3.1 Baseline Specification Results

The impulse responses are presented in Figure 1.3. The impulse responses presented are scaled to a one standard deviation increase in the log level of Reserve Balances.\(^\footnote{\text{Although these are the results from a linear model, the impulse responses can be scaled to reflect asset purchases of a particular amount during the three rounds of QE.}}\) The results indicate that in response to an asset purchase shock, real GDP and consumer prices increase by 0.79 and 0.65 percentage points, respectively. There is a 3 basis point reduction in IOER, and a 58 basis point reduction in the 10 year Treasury yield. The small reduction in IOER is consistent with the observed data regarding this variable, in that there was little variation over the sample period.

The responses of the banking sector variables are consistent with other VAR studies addressing bank lending behavior (Abbate and Thaler, 2015; Afanasyeva, and...
Figure 1.3: Unconventional Monetary Policy Shock

Note: This figure shows the median impulse responses in response to a one standard deviation increase in Reserve Balances, together with the 68% Bayesian credibility sets. The posterior estimates are acquired by employing a non-informative Wishart prior with 10,000 Monte Carlo draws used to generate the responses.

Guntner; 2014; Neuenkirch and Nockel, 2018). The results suggest that banks reduce their lending standards by 10.19 percentage points, and lending margins are reduced by 1.96 basis points.\(^{11}\) These results indicate that in response to a monetary policy shock, banks lower their lending standards in order to keep lending margins stable (Neuenkirch and Nockel; 2018). Bekaert et al. (2013) also suggest this behavior in arguing the existence of a close relationship between Federal Open Market Committee announcements and measured risk, suggesting banks drastically adjust their lending behavior in response to policy interventions at the Fed.

The implications of these results being qualitatively similar to Neuenkirch and Nockel (2018) indicate that as banks attempt to stabilize lending margins, they are unsuccessful in doing so, as the Bayesian credibility bands for the response in lending

\(^{11}\)I report the peak median impulse responses in the discussion of these results.
Table 1.2: Banking Variable Responses to Monetary Policy Shock (Scaled to Reserve Balance Increase in Each Round of QE)

<table>
<thead>
<tr>
<th>Variable</th>
<th>QE:I</th>
<th>QE:II</th>
<th>QE:III</th>
<th>QE:I-III</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Percentage Points)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lending Margins</td>
<td>-96.02</td>
<td>-80.04</td>
<td>-84.02</td>
<td>-142.51</td>
</tr>
<tr>
<td>(Basis Points)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: This table shows the peak responses in lending standards and lending margins for the unconventional monetary policy shock scaled to align with the magnitude of the increases in reserve balances during each round of Quantitative Easing.

Lending margins suggest more than 68% of the accepted MCMC draws indicate a compression in lending margins, and thus a reduction in bank profitability through lending.

To assess the magnitudes of the responses of the banking sector variables to each round of QE, Table 1.2 presents the peak median impulse responses to an asset purchase shock consistent with QEI-III individually, as well as the responses over the entire period in which QE was implemented. The first round of QE, which spanned Q4:2008 to Q2:2010, suggests lending standards were reduced by 17.79 percentage points, while lending margins compressed by nearly 1% (96 basis points). This was the most aggressive round of asset purchases, and banking sector variables appear to respond accordingly. The table also indicates that over the three rounds of QE, the total effect on lending standards was a 26.41 basis point reduction, and the total impact on lending margins was 142.41 basis points.
1.3.2 Conventional Monetary Policy Responses

This subsection estimates and identifies a VAR for the conventional monetary policy regime spanning Q2:1990-Q3:2008. As the Federal Reserve’s policy tools changed after the onset of the Financial Crisis of 2007/08, estimation and identification of a VAR for this period must be altered to reflect the monetary and financial conditions over the course of the sample period. As such, I alter one variable in the VAR specification by replacing IOER with the Federal Funds Rate. In addition, I identify a shock to the policy rate equation (the Federal Funds Rate) in lieu of the log level of excess reserves by placing a negative sign restriction on the Federal Funds Rate. The VAR is estimated with a lag length of 2.

The results are presented in Figure 1.4, and suggest that in response to a one standard deviation reduction in the Federal Funds Rate, equal to a 22 basis point reduction, real GDP and consumer prices increase by 0.21 and 0.10 percentage points, respectively, and the 10 Year Treasury Yield is reduced by one percent. The banking sector variables indicate a reduction in bank lending standards by 26.27 percentage points and lending margins compress by 6.96 basis points.

As in the unconventional monetary policy regime, the results in this subsection further support the claims by Neuenkirch and Nockel (2018) in that banks lower lending standards to stabilize profit margins, however are unsuccessful in doing so. These results are consistent with Rajan (2006), Buch et al. (2014), and Neuenkirch and Nockel (2018). The impulse responses show similar qualitative movements compared to the results of Neuenkirch and Nockel (2018), whose study is applied only to the Euro Area responses to asset purchase shocks at the ECB. Despite the similarities in qualitative responses to the baseline VAR specification, comparison of the impulse responses is not possible, as identification schemes vary across regimes. Therefore, to
Note: This figure shows the median impulse responses in response to a one standard deviation increase in Reserve Balances, together with the 68% Bayesian credibility sets. The posterior estimates are acquired by employing a non-informative Wishart prior with 10,000 Monte Carlo draws used to generate the responses.

compare responses between both regimes, there must be a consistent identification strategy that is employed across each sample period. The following section develops a number of counterfactual interest rates for the unconventional monetary regime to compare shocks in a consistent manner to assess variations in risk-taking by banks during periods with vastly different structural frameworks regarding monetary policy and regulatory overhauls of the financial sector after 2008.
Table 1.3: Banking Variable Responses to Monetary Policy Shock (25 and 50 Basis Point Reduction in the Federal Funds Rate)

<table>
<thead>
<tr>
<th>Variable</th>
<th>25 bps</th>
<th>50 bps</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lending Standards (Percentage Points)</td>
<td>-29.57</td>
<td>-59.14</td>
</tr>
<tr>
<td>Lending Margins (Basis Points)</td>
<td>-78.39</td>
<td>-156.81</td>
</tr>
</tbody>
</table>

Note: This table shows the peak responses in lending standards and lending margins for a conventional monetary policy shock scaled to align with the magnitude of the decreases in the Federal Funds Rate.

1.4 Comparison Between Monetary Policy Regimes

This section presents an alternative method of specifying the unconventional monetary policy VAR with a number of alternative interest rates to serve as counterfactual policy rates used by the Fed in lieu of reserve balances. I identify monetary policy shocks through a cut in the Fed’s policy rate, rather than the reserve balance equation. I construct a Taylor Rule to serve as a counterfactual rate, as well employ as the Shadow Federal Funds Rate developed by Wu and Xia (2016). This allows for a more appropriate comparison across regimes to understand the role the risk channel played in each regime.

1.4.1 Alternative Interest Rates

In this subsection, I employ a set of interest rates that allow me to compare responses in the banking sector to asset purchase shocks across two different monetary policy regimes. In the previous section, the VARs had differing identification strategies, as the innovations were imposed on the residual vectors contained in differ-
ent equations in the model. To compare changes in risk-taking following a monetary policy shock, it is necessary to construct a counterfactual interest rate to reflect monetary policy should the FOMC have opted to engage in negative interest rate policies rather than using QE as a viable alternative. By including these counterfactual rates, I can identify shocks to the policy rate equation in both VAR models and analyze banking sector responses in a more logically consistent manner.

### 1.4.1.1 Bernanke’s Taylor Rule

The first alternative interest rate I include is a Taylor Rule. By using a Taylor Rule in place of IOER, I can include a counterfactual policy rate in which there is no ZLB, and Fed policy measures can achieve negative nominal interest rates. The Taylor Rule takes the form

\[
r_t = r_t^* + \alpha_\pi(\pi_t - \pi_t^*) + \alpha_y(y_t - y_t^*),
\]

(1.6)
Figure 1.6: Impulse Responses to Monetary Policy Shock Using Bernanke’s Taylor Rule

Note: This figure shows the median impulse responses in response to a one standard deviation reduction in the Taylor Rule, together with the 68% Bayesian credibility sets. The posterior estimates are acquired by employing a non-informative Wishart prior with 10,000 Monte Carlo draws used to generate the responses.

where $r_t^*$ is the target Federal Funds Rate, $\pi_t$ is core PCE inflation, $\pi_t^*$ is the Fed’s target inflation rate, which is 2.0%, $\alpha_{\pi}$ is the weight the central bank places on deviations of inflation from their target, $y_t$ is the growth rate in real GDP, $y_t^*$ is the growth rate in potential real GDP, and $\alpha_y$ is the weight placed on deviations of output from potential GDP. While the Taylor Rule is typically formulated using coefficients of 0.5 for both inflation and output deviations, Yellen (2012) and Bernanke (2015) suggest a more appropriate version of the rule during the unconventional monetary policy regime would be to assign a weight of 0.25 on the inflation gap, and 1.00 on the output gap, rather than 0.5 for each. During this formulation, I only use data that was available to policymakers at the time. Because many of these estimates are revised over time, it is pertinent to ensure that real-time data is used in the computations.
when developing a counterfactual interest rate for policy choices. Figure 1.5 presents the Federal Funds rate and the Taylor Rule I compute using $\alpha_\pi = 0.25$ and $\alpha_y = 1.00$.

The identification scheme in this specification, and all other alternative interest rate specifications that follow, still imposes a one standard deviation shock to the reserve balance equation in the VAR, and is thus entirely unchanged from the baseline estimation. The only difference between the VARs in this subsection relative to the baseline specification is the use of the alternative policy rate.

The results are presented in Figure 1.6. The peak responses of GDP and consumer prices, are similar to the responses presented in Figure 1.3, yet with more lower bound flexibility available in the short-term policy rate, long-term yields are reduced by less, experiencing a less than 40 basis point reduction, as compared to a 60 basis point reduction in the baseline specification.

As there are different effects being exerted via the term structure of interest rates, the responses of the banking sector variables change somewhat as well. While lending standards are only reduced by one percentage point more than in Figure 1.3, lending margins compress by only 50 basis points, as compared to 196 basis points in the baseline model. Note that these findings are likely not just the result of a different interest rate being employed for the Fed’s policy rate, but also that of the source of the shock and the scaling of the impulse response functions across different equations.

When the results are scaled to a 25 (or 50) basis point cut in the Taylor Rule used by Bernanke, lending standards are reduced by 19.63 (39.26) percentage points. Lending margins, however are compressed by 103.37 (206.74) basis points.
1.4.1.2 Shadow Federal Funds Rate

As a robustness check on the findings of the counterfactual interest rate analysis, I include an interest rate not computed via a Taylor Rule; the Shadow Federal Funds Rate constructed via a term structure of the interest rates model by Wu and Xia (2016). Figure 1.7 compares the Shadow Federal Funds Rate with the effective Federal Funds Rate. This shadow rate is employed to reflect unconventional monetary policy as if it were transmitted through short term rates more than long term rates, with flexibility to allow for an effective lower bound below zero.\footnote{Neuenkirch and Nockel (2018) employ this as a counterfactual interest rate in the Euro Area, arguing more lower bound flexibility via this shadow rate serves as an alternative to Quantitative Easing for more adequate comparison between the two monetary policy regimes used by the ECB. I employ this shadow rate for the U.S. as a similar exercise.}

The term structure of the interest rates model used to compute the Shadow Federal Funds Rate is calibrated in a manner such that the Shadow Rate and the Effective Federal Funds are equivalent during the conventional monetary policy regime and after the December 2015 interest rate hike. This, this rate differs from the Effective Federal Funds Rate only when the Effective rate is at or below 25 basis points.

The results using the Shadow Federal Funds Rate as the Fed’s policy rate are presented in Figure 1.8. A one-standard deviation reduction in the Shadow Federal Funds Rate is a 40 basis point cut, requiring a sizable re-scaling to compare the peak median impulse responses across the different specifications. Compared to the Bernanke Taylor Rule specification, the peak reduction in the policy rate is 11 basis points.

The responses of real GDP and consumer prices are still somewhat consistent with the results from the previous unconventional monetary policy specifications in this paper. The reduction in the 10 Year Treasury yield is roughly 50 basis points.
The banking sector responses suggest a 10.75 percentage point reduction in lending standards, and a 130 basis point compression in lending margins. This suggests that banks take less risk, yet experience less profitability in response to a monetary policy shock. As in the other Taylor Rule specifications, adequate comparison will require a re-scaling of the impulse responses, which are provided in section 1.4.3.

When the results are scaled to a 25 (or 50) basis point cut in the Shadow Rate, lending standards are reduced by 6.75 (13.50) percentage points. Lending margins, however are compressed by 81.25 (162.50) basis points. This shows a much smaller reduction in lending standards compared to the Bernanke Taylor Rule.

The results show that as there is more variability in the policy rate (compared to interest on excess reserves or the Bernanke Taylor Rule), banks reduce their lending standards by less, and there is a more substantial reduction in lending margins. This lends evidence to suggest that as banks will take risk to stabilize profit margins, however the term structure of the interest rates plays a substantial role in the amount by which lending margins compress.
1.4.2 Forecast Error Variance Decomposition

To assess the role the risk channel played in each monetary regime, I employ a forecast error variance decomposition (FEVD). I compare the FEVD plots for each regime, as provided in Figures 1.9 and 1.10. The FEVD plot for the unconventional monetary policy regime uses the baseline model, as this specification and accompanying identification method is consistent with the policy tools used by the Federal Reserve during Quantitative Easing. The FEVD plots for the alternative interest rates used to compare risk across the two monetary policy regimes are presented in Appendix A.2.

The FEVD analysis suggests despite the larger cuts in lending standards during the conventional monetary policy regime relative to the unconventional regime, a monetary policy shock explains 15% of the variation in the conventional period, and 21% of the variance in the unconventional regime. The variance in lending margins
explained by a monetary policy shock suggest similar behavior, with 16% of the variation in lending margins explained during the conventional monetary policy regime, and 23% of the variation in lending margins explained during the unconventional monetary policy regime.

The FEVDs therefore suggest that, while the differences are somewhat small, the risk channel of monetary policy appears to have operated more during the unconventional monetary policy regime than the conventional period. This is consistent with other measures of risk argued by Weale and Wieladek (2016) to serve as indicators of uncertainty in the economy. For example, the VIX, AAA-BBB bond spreads, and household uncertainty indicators all showed substantially more variability during the unconventional monetary policy regime relative to the conventional period. As such, economic agents are more observant of risk following the Financial Crisis than before, and thus monetary policy shocks are more likely to signal economic stabilization in a regime more sensitive to risk.
The FEVD plots for the alternative interest rates used in the comparison of risk across monetary policy regimes suggest similar results to the baseline specification’s FEVD plots, with implications that the risk channel played a larger role in the unconventional monetary policy regime than the conventional period. Using the Bernanke Taylor Rule, the FEVD plots indicate that 15% of the variance in lending standards and 22% of the variance in lending margins is explained by a monetary policy shock. The Shadow Federal Funds Rate specification provides additional evidence that the risk channel played a larger role in the conventional regime, with 40% of the variance in lending standards and 25% of the variance in lending margins being explained by a policy rate reduction. Thus, across all specifications used in this paper, the findings indicate the risk channel played a more important role in the unconventional monetary policy regime than the conventional monetary regime, in which the Federal Funds Rate was used as the Fed’s policy tool.
Table 1.4: Banking Variable Responses to Monetary Policy Shock

<table>
<thead>
<tr>
<th>Variable</th>
<th>Period</th>
<th>25 bps Cut in Policy Rate</th>
<th>50 bps Cut in Policy Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lending Standards</td>
<td>Conventional</td>
<td>-29.57</td>
<td>-59.14</td>
</tr>
<tr>
<td>(Percentage Points)</td>
<td>Unconventional (Bernanke)</td>
<td>-19.63</td>
<td>-39.26</td>
</tr>
<tr>
<td></td>
<td>Unconventional (Shadow Rate)</td>
<td>-6.75</td>
<td>-13.50</td>
</tr>
<tr>
<td>Lending Margins</td>
<td>Conventional</td>
<td>-38.42</td>
<td>-76.84</td>
</tr>
<tr>
<td>(Basis Points)</td>
<td>Unconventional (Bernanke)</td>
<td>-103.37</td>
<td>-206.74</td>
</tr>
<tr>
<td></td>
<td>Unconventional (Shadow Rate)</td>
<td>-81.25</td>
<td>-162.50</td>
</tr>
</tbody>
</table>

Note: This table shows the peak responses in lending standards and lending margins for both conventional and unconventional monetary policy regimes.

1.4.3 Policy Implications

The results of the peak median impulse responses scaled to a 25 (50) basis point cut in the Fed’s policy rate are presented in Table 1.4. When the impulse responses from the alternative interest rate specifications are scaled to either a 25 (50) basis point cut in the Federal Reserve’s policy rate, comparison across rates suggest that as there is more lower bound flexibility, banks respond with less risk via a reduction in lending standards, yet also experience a larger compression in lending margins. However, the variance in the policy rates appears to play a substantial role in the response in the banking sector variables. The Shadow Federal Funds Rate allows for less lower bound flexibility (minimum of 3.25%) than the Bernanke Taylor Rule (minimum of 5.75%), however also displays an upward spike once the Effective Federal Funds Rate reached the ZLB.

Comparing the banking sector responses across the two monetary policy regimes and the alternative interest rate variables used in lieu of Quantitative Easing for unconventional monetary policy, the results indicate banks take less risk via a lending standard reduction in the unconventional monetary policy regime. During the con-
ventional monetary policy regime, a 25 basis point cut in the Fed Funds rate is consistent with a 29.57 (59.14) percentage point reduction in lending standards along with a 38.42 (76.84) basis point compression in lending margins. The unconventional regime suggests that under the Bernanke Taylor Rule, banks reduce lending standards by 19.63 (39.26) percentage points, and experience a 103.37 (206.74) percentage point compression in lending margins. The Shadow Federal Funds Rate specification shows a 6.75 (13.50) reduction in lending standards accompanied by an 81.25 (162.50) compression in lending margins. Despite the large difference in lending standards between these two interest rates there is a similarity in lending margin compression between these two specification.

The smaller reduction in lending standard reduction in the unconventional monetary policy regime is consistent with the data on the total value of loans issued by banks in the post-Financial Crisis period. With interest paid on excess reserves, in conjunction with a perceived lack of credit-worthy borrowers following the initiation of QE as the Fed's policy tool, the level of Commercial and Industrial loans were reduced, and continued to fall until the beginning QE:II in Q2:2011. As such, if banks are unwilling to reduce lending standards after the Financial Crisis relative to before, the larger compression in lending margins suggests that while banks are unsuccessful in stabilizing their lending margins, the reduction in lending standards plays some role in the response of lending margins.

When considering both the alternative interest rates and the FEVD plots, the evidence suggests the Federal Reserve Bank would be well-served to take the risk channel into consideration when drafting future monetary policy measures. The empirical evidence regarding other transmission mechanisms during QE indicate the portfolio rebalancing channel operated in tandem with the risk channel. As the portfolio rebalancing channel operates through a reduction in long term yield with
increases in asset prices and the risk channel is activated through perceptions in risk and uncertainty in durable consumer goods markets, financial markets (Weale and Wieladek; 2016) and the banking sector, the dual mandate may not be sufficient to adequately stabilize the economy via monetary policy measures enacted by the Fed. The dual mandate, which currently exists to minimize unemployment and maintain an annual inflation rate (via the Personal Consumption Expenditures Price Index, which does not include asset prices) of 2%, does not explicitly address risk, uncertainty, or asset price variation. Thus, as lending behavior can significantly respond to monetary policy shocks, if the Fed does not address this particular transmission mechanism, there may be a buildup of risk in the credit system that is not being considered in the current monetary policy framework. Thus, a reappraisal of the dual mandate may be necessary during the current monetary policy regime.
1.5 Conclusion

This paper investigates the role the risk channel of monetary policy plays in bank lending behavior in the determination of compressions in bank lending margins. In response to the Great Recession, the United States Federal Reserve engaged in three rounds of Quantitative Easing as a measure of unconventional monetary policy designed to influence real economic activity while short term rates were at the zero lower bound. I estimate vector autoregression (VAR) models identified with a combination of sign and zero restrictions to compare responses in bank lending standards to expansionary monetary shocks during different policy regimes to address the changes in risk-taking and the ability to stabilize bank lending margins. My first VAR estimation for the unconventional regime identifies a shock to reserve balances, however to compare the amounts of risk banks are willing to take to stabilize lending margins across both regimes, I estimate a number of VARs with alternative interest rates to act as a substitute for QE, and identify shocks to the Fed’s policy rate equation. When compared across regimes, I find banks take less risk during the unconventional monetary policy regime compared to the conventional regime. While banks take more risk in the conventional regime, my results indicate a much larger compression in lending margins during the unconventional regime. This is consistent with the data regarding bank loans after the Financial Crisis of 2007/08. The findings are robust across various specifications, and the forecast error variance decompositions for each specification indicate the risk channel plays a larger role in the unconventional monetary policy regime.

My results have significant policy implications with respect to the current structure of monetary policy in the United States. The Federal Reserve currently operates under the dual mandate, which is to minimize unemployment and maintain
a stable annualized inflation rate of 2%. As the empirical evidence suggests the real economy responded through transmission mechanisms of unconventional monetary policy that operated via substantial movements in financial market and banking sector variables, the Federal Reserve would be well-suited to consider the risk channel in future policy initiatives. Failure to do so may result in a buildup of risk in the credit system, leading to future financial crises. As the Fed’s current price index used for monitoring of inflation does not include asset prices, it would be prudent to at least consider equity markets when enacting future monetary policy measures.

Research in this particular channel of monetary policy opens a number of avenues for future projects. First, it would be prudent to more accurately assess the role of moral hazard by separating the Federal Reserve Bank’s balance sheet during the unconventional monetary policy regime to individually identify shocks to their holdings of Treasury and Mortgage Backed Securities. As the Fed’s asset purchases during QE were unprecedented in both size and composition, addressing shocks to these two components of their balance sheet would address how perceptions of risk responded to changes across both public and private debt acquisition. Second, further investigation to the response of perceptions of risk in both financial markets and the banking sector through different counterfactual interest rates that allow for variations in lower bound flexibility in policy rates in lieu of QE would provide evidence regarding the role the term structure of interest rates plays in determining how the risk channel operates during the unconventional monetary policy regime. Third, in using numerous counterfactual interest rates across different monetary policy regimes, an alternative estimation procedure may be to use a non-linear, state dependent VAR to include the full sample in one model estimation, rather than separating them into two separate VARs. Finally, as the risk channel can operate through consumer confidence, financial market, and banking sector sub-channels, it would be interesting to identify the role
each plays in the overall activation of this transmission mechanism of monetary policy in the United States.
Bibliography


Chapter 2

Spillovers of United States Quantitative Easing: What are the Foreign Monetary Policy Responses to US Monetary Policy Shocks?

2.1 Introduction

The decade following the Financial Crisis of 2008 witnessed the introduction of unconventional monetary policy (UMP) conducted by various central banks when short term nominal interest rates approached the zero lower bound (ZLB). United States UMP measures were composed of programs such as Quantitative Easing (QE) and Operation Twist. Between 2009 and 2014, the Federal Reserve implemented three rounds of QE, ultimately purchasing $4.2 trillion in Treasury and Mortgage Backed Securities, as presented in Figure 2.1. The goals of QE were to lend to financial institutions, directly provide liquidity to markets affected by the financial crisis, and purchase long term Treasury and mortgage-backed securities to lower yield spreads, encourage lending, maintain their inflation target, and ultimately stimulate real economic activity.
Given the vast financial and trade integration with the global economy, implications regarding the effects of QE extend well beyond United States borders. Rey (2013), Bekaert et al. (2013), Miranda-Agrippino and Rey (2015), Passari and Rey (2015) and Georgiadis (2016) argue global events are largely determined by United States monetary policy measures. However, recent evidence suggests heterogeneous responses between advanced economics (AE) and emerging market economies (EME).

In a flexible exchange rate world, the Mundell Fleming-Dornbusch model suggests expansionary monetary policy in the home economy generates an exchange rate depreciation, reducing the prices of home goods relative to foreign goods. This reduction in relative prices leads to increases in the demand for home goods by both domestic and foreign countries. Should foreign central banks fail to respond through expansionary monetary policy to mitigate spillover effects that travel through the exchange rate, a “beggar-thy-neighbor” effect ensues, in which foreign output falls as a result of the increase in demand for the domestically produced goods.

The empirical evidence does not favor such an effect, however. Eichenbaum
and Evans (1995), Kim and Roubini (2000), Kim (2001), Faust and Rogers (2003), Faust et al. (2003), Canova (2005), Nobili and Neri (2006), Mackowiak (2007), Blue- dohn and Bowdler (2011), Abdelfaki and Feki (2012), and Aizenman, Chinn, and Ito (2016) find evidence of increases in foreign output and prices following expansionary monetary policy in the United States, however the magnitude of these increases are at least partially dependent upon their levels of trade integration with the United States. The movements of foreign macroeconomic variables are consistent with a “prosper-thy-neighbor” effect, in which foreign central banks align themselves with monetary policy measures set by the United States.

There is a wealth of dynamic stochastic general equilibrium (DSGE) literature addressing foreign central bank responses after monetary expansion in a home country. Obstfeld and Rogoff (1995) develop a micro founded open economy New Keynesian DSGE model with nominal rigidities to show a beggar-thy-neighbor effect can ensue following a monetary policy shock originating in the home country. Carida et al. (2002) further expand upon these models to incorporate inflation/output tradeoffs with international spillover effects to illustrate the benefits from monetary policy coordination between foreign central banks. Levine, Pearlman, and Pierse (2007) introduce ZLB constraints, finding welfare gains from commitment to policy announcements and cooperation between foreign monetary authorities. Alpanda and Kabaca’s (2017) DSGE is developed and calibrated specifically for the QE period in the United States. Their model incorporates real and nominal rigidities with portfolio rebalancing effects to show a depreciation in yield from QE generating currency appreciation pressures abroad. Foreign monetary policy responses lead to lower bond yields, stimulating the global economy. They additionally show the model produces similar qualitative effects for both pre- and post-QE periods, with the pre-crisis period generating substantially smaller quantitative responses. Kolasa and Wesolowski
(2018) develop a DSGE in which they show QE policies originating in AEs generate substantially different spillover effects when compared to emerging economies EMEs. While AEs tend to receive positive spillovers in output, EME responses indicate temporary decreases in aggregate output; providing an implication for the benefits of EME central bank counter cyclical monetary policy measures to prevent beggar-thy-neighbor effects from materializing.

The empirical studies of the impacts of United States QE support the results of Alpanda and Kabaca (2015) and Kolasa and Wesolowski (2018), in that foreign
central banks respond with asset purchases of their own to stimulate their home economies. Chen et al. (2012), Eichengreen (2013), and Georgiadis (2016) suggest favorable responses of AEs to QE, with increases in both output and inflation, while EMEs have much more diverse effects. There are two distinct and opposing views on the influence of QE in the developing world. Lavigne et al. (2014) argue QE was necessary to prevent declines in United States production during the recession to allow exports to meet the product demands of foreign economies, thus stimulating real activity in EMEs. Chen et al. (2012) and Barroso et al. (2015) suggest QE led to higher inflation in many EMEs, especially in Latin America and Asia.

With respect to the mechanisms of monetary policy, economic theory implies a number of ways in which asset purchases may affect the real economy. First, monetary policy can spillover through the exchange rate, as suggested by the Mundell Fleming-Dornbusch model. QE generates spillovers to foreign markets through devaluation of the dollar relative to other currencies. Eichenbaum and Evans (1995) provide evidence for this channel as a potential transmission mechanism of United States monetary policy into foreign economies.

A second potential mechanism operates through bond yields. As discussed by Alpanda and Kabaca (2015), appreciation pressure on foreign currency can lead to a reduction in interest rates in the rest of the world as a result of the decline in the term premium component of United States long term rates. The portfolio rebalance channel is activated when lower long term United States bond yields induce foreign investors to alter the composition of their portfolio holdings through an increased demand for substitutable assets. Ultimately, this channel lowers risk premia and boosts asset prices, leading to reductions in yield for foreign economies, ultimately easing financial conditions in both AEs and EMEs. Evidence for this channel is provided by Vayanos and Vila (2009), Albertazzi, Becker, and Boucinha (2012), and
This paper investigates the monetary policy responses to United States QE in twelve AEs and twelve EMEs. My results show AEs and EMEs both follow in kind with United States monetary expansions. I find that QE affects long term yields in AEs, and short term yields in EMEs. Figure 2.2 presents the average of short and long term interest rates in AEs and EMEs. Many AEs faced policy constraints by short term interest rates being at or near the ZLB, whereas EMEs had much higher short term rates. Thus, EMEs were able to defer to conventional monetary policy measures to affect short term yields while AEs were not.

I also find AEs are likely to experience larger responses in output, while EMEs respond more through increases in consumer prices, confirming the view held by Chen et al. (2012) and Barroso et al. (2015). I find the largest increases in consumer prices in Latin American countries and Turkey. I investigate the relative contribution of a QE shock to foreign variables, finding EME monetary policy is more likely to be influenced than AE policy. My results are robust to changes in the specification and identifying restrictions.

I contribute to the literature in five ways. First, while many previous studies such as Kim and Roubini (2000), Kim (2001), Faust and Rogers (2003), Faust et al. (2003), Canova (2005), Nobili and Neri (2006), Mackowiak (2007), Bluedorn and Bowdler (2011), and Abdelfaki and Feki (2012) investigate the effects of global output spillovers resulting from United States monetary policy, they are modeled using bilateral two-country VAR models. These models include United States variables and the variables of one other economy. While the results of these studies suggest United States monetary policy has substantial spillover effects in both AEs and EMEs, they suffer from methodological constraints, as their structure does not allow for the multilateral nature of intertwined cross-country and global effects. As
United States monetary policy may influence global economic conditions, there are third party and feedback effects that cannot be captured with a traditional bilateral VAR model. In adopting the global vector autoregression (GVAR) methodology developed by Pesaran, Schuermann, and Weiner (2004) and Pesaran and Smith (2006), I allow for a more complete analysis of foreign economy responses to spillovers from QE in the United States.

Second, I use Bayesian methods to identify global spillovers to a United States QE shock with a combination of sign and zero restrictions. The conventional identification scheme for a GVAR is to employ a generalized impulse response function, which does not allow for the inclusion of any \textit{a priori} economic theory, however as discussed by Pesaran (2007), it serves as an alternative to imposing an implausible number of identifying restrictions that are not necessarily justified in the international macro literature. Recently, the GVAR literature has adopted the method of sign restrictions identification to assess spillovers of various economic shocks.\footnote{Chudik and Fratzscher (2011), Georgiadis (2016), and Anaya, Hachula, and Offermanns (2016) employ GVARs identified with sign and zero restrictions to investigate spillover effects of developments within the United States policy after the 2008 financial crisis.} Sign identification has an added advantage of alleviating the requirement of a large number of identifying restrictions to identify shocks of interest.

Third, I investigate foreign monetary policy responses to QE. While many studies investigate foreign central bank responses to conventional monetary policy measures from the Fed, the literature on UMP spillover responses is relatively scarce.\footnote{See Eichenbaum and Evans (1995), Kim and Roubini (2001), Faust and Rogers (2003), and Blue-dorn and Bowdler (2011) for foreign central bank responses to United States conventional monetary policy measures.} I provide evidence regarding the responses of foreign central banks to QE in the United States, where AEs experience large responses in production and EMEs have more sizable increases in consumer prices. In addition, I find central banks with
inflation targeting policies have more stable responses than central banks with no de jure targeting policy after a QE shock. I also group economies by their exchange rate characteristics. I find that while economies with floating exchange rates have less aggressive monetary policy responses than managed exchange rate regimes, floating exchange rates do not serve as a buffer to allow central banks to enjoy complete monetary policy independence. These findings support the conclusions of Rey (2013) with respect to the Mundell Fleming trilemma, in which a central bank may have two of the three: fixed exchange rates, free capital flows, or monetary policy independence.

Fourth, I assess the relative importance of a United States QE shock to foreign variables via forecast error variance decomposition (FEVD) analysis. While I find that spillover effects appear to propagate through bond yield and real exchange rate channels for both AEs and EMEs, a QE shock from the United States explains more variance in EME monetary variables than AEs, suggesting QE spillovers play a larger role in the determination of EME monetary policy than AEs.

Finally, I shed light on the possible channels through which QE may have been propagated. First, as discussed by Vayanos and Vila (2009), Weale and Wieladek (2016), I find evidence of a portfolio rebalance channel in many AEs and a small number of EMEs. I also find EMEs operate through short term interest rate channels, while AEs respond more through long term interest rates. Next, I find evidence of activation of an exchange rate channel in nearly all economies in my sample. My results are consistent with the existing literature.4

The remainder of this paper is as follows; Section 2.2 introduces the GVAR model, data used in my estimations, and an explanation of identification through


4See D’Amico and King (2010), Gagnon et al. (2012), Hamilton and Wu (2012), and Bauer and Rudebusch (2014).
sign and zero restrictions. Section 2.3 presents the results with impulse responses, forecast error variance decomposition analysis, and a number of robustness checks, and Section 3.6 concludes.
2.2 Estimating Spillovers of Quantitative Easing

To assess spillover effects of QE and foreign central bank responses, I employ a GVAR developed by Pesaran et al. (2004). The GVAR method employs a two step procedure. In the first step, I estimate $N$ country-specific VAR models with exogenous variables (VAR-X). In the second step I combine and stack the VAR-X estimate to solve them as one large global model in which the foreign blocks of exogenous variables for every country are now treated as endogenous and weighted by proportional trade flows. Following my discussion of the reduced form GVAR estimation in this paper, I present the data and the strategies used to identify a United States QE shock via sign and zero restrictions.

2.2.1 GVAR Methodology

The motivation of a GVAR is to estimate a VAR of global dimension containing $i = 1, ..., N$ countries, each with $k_i$ variables such that $k = \sum_{i=1}^{N} k_i$. The VAR takes the form

$$y_t = c + \sum_{\ell=1}^{p} A_{\ell} y_{t-\ell} + u_t,$$

(2.1)

where $c$ is an $Nk \times 1$ vector of constants, $y_t = \left(y_{1,t}', y_{2,t}', ..., y_{N,t}'\right)'$ is the vector of $k$ endogenous variables stacked over $N$ countries, $A_{\ell}$ is a $k \times k$ matrix of autoregressive coefficients, and $u_t$ is a $k \times 1$ vector of reduced form residuals. As the number of parameters will be large, even with a small $N$, estimation of this large scale VAR with a short time sample is not possible.

Pesaran and Smith (2007) propose a large scale VAR by estimating a conditional VAR-X model for each of the $N$ economies in the sample, which are linked
linked via bilateral trade flows. The conditional VAR-X for each individual country $i = 1, 2, ..., N$ is

$$y_{i,t} = c_i + \sum_{\ell=1}^{p_i} A_{i,\ell} y_{i,t-\ell} + \sum_{\ell=1}^{q_i} A^*_{i,\ell} y^*_{i,t-\ell} + u_{i,t},$$  \hspace{1cm} (2.2)$$

where $y_{i,t}$ is a vector of $k_i$ endogenous variables, $A_{i,\ell}$ is a $k_i \times k_i$ matrix of lagged autoregressive coefficients, $A^*_{i,\ell}$ is a matrix of coefficients for the exogenous foreign variables, and $y^*_{i,t}$ is a vector of $k$ country-specific weakly exogenous foreign variables.

The distinguishing feature of GVAR estimation is in the set of foreign exogenous variables $y^*_{i,t}$, which are expressed as weighted averages of other countries’ variables via bilateral trade weights $w_{i,j}$ such that

$$y^*_{i,t} = \sum_{j=1}^{N} w_{i,j} y_{j,t},$$  \hspace{1cm} (2.3)$$

where

$$\sum_{j=1}^{N} w_{i,j} = 1,$$  \hspace{1cm} (2.4)$$

and $w_{i,j} \geq 0 \ \forall \ i \neq j$ and $w_{ii} = 0$. The bilateral trade weights capture the exposure of country $i$ to country $j$ as a share of country $i$’s total trade flows. The foreign variables $y^*_{i,t}$ are assumed to be weakly exogenous with respect to the parameters in the VAR-X models given by Equation 2.2.

After a VAR-X is estimated for each of the $N$ countries in the sample, the coefficient estimates are combined and stacked to form one large global VAR. This global form of the VAR allows for the existence of interdependencies between each set of country-specific domestic variables, treating every variable as endogenous in the reduced-form GVAR.
If I let $y_t$ be the $k \times 1$ vector of all observable variables, I stack the country specific conditional models to produce

$$y_t = c + \sum_{\ell=1}^{P} A_{\ell} y_{t-\ell} + u_t,$$

where

$$u_t' = [u_{1,t}, u_{2,t}, \ldots, u_{N,t}'].$$

and

$$A_{\ell}' = [A_{1,\ell} W_1, A_{2,\ell} W_2, \ldots, A_{N,\ell} W_N]' .$$

The global solution is equivalent to that of the reduced form VAR expressed in Equation 2.1, but with numerous interlinkages between the $k$ variables and $N$ countries. The global VAR in reduced form can be used to perform standard VAR analysis and obtain the structural impulse response functions for statistical inference. The method of identification via sign and zero restrictions in this paper is presented in subsection 2.2.4.

### 2.2.2 Data

All VAR-X models in this paper are estimated with monthly data for the period when asset purchases were an active policy tool at the Federal Reserve (January 2007 to October 2014). Additionally, I use a lag length of 1 for each VAR-X in my analysis. With the inclusion of the United States, my sample comprises twenty five monetary areas listed in Table 2.1. A description of the data sources is provided in Table 7.

The United States vector of endogenous variables $y_{1,t}$ I estimate is composed
Table 2.1: Monetary Areas Included in Analysis

<table>
<thead>
<tr>
<th>Advanced Economies</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States</td>
</tr>
<tr>
<td>Australia</td>
</tr>
<tr>
<td>Canada</td>
</tr>
<tr>
<td>Denmark</td>
</tr>
<tr>
<td>Eurozone</td>
</tr>
<tr>
<td>Iceland</td>
</tr>
<tr>
<td>Israel</td>
</tr>
<tr>
<td>Japan</td>
</tr>
<tr>
<td>New Zealand</td>
</tr>
<tr>
<td>Norway</td>
</tr>
<tr>
<td>Sweden</td>
</tr>
<tr>
<td>Switzerland</td>
</tr>
<tr>
<td>United Kingdom</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Emerging Market Economies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brazil</td>
</tr>
<tr>
<td>Chile</td>
</tr>
<tr>
<td>China</td>
</tr>
<tr>
<td>Colombia</td>
</tr>
<tr>
<td>Czech Rep.</td>
</tr>
<tr>
<td>Hungary</td>
</tr>
<tr>
<td>India</td>
</tr>
<tr>
<td>Mexico</td>
</tr>
<tr>
<td>Poland</td>
</tr>
<tr>
<td>Russia</td>
</tr>
<tr>
<td>South Korea</td>
</tr>
<tr>
<td>Turkey</td>
</tr>
</tbody>
</table>

of the log of the Industrial Production Index, the log of the Personal Consumption Expenditures Index, the log of a narrow money index (used to reflect the monetary base), the 90 Day Treasury yield, the 10 Year Treasury yield, the log of the S&P 500 Stock Price Index (in real terms, using January 2009 as the base price), and the real effective exchange rate of the U.S. dollar against all other major trading currencies.\(^5\)

The vector of foreign variables enters \(\mathbf{y}_{\mathbf{1},t}^*\) Equation 2.2, containing the log of industrial production, log of the price level, the log of a narrow monetary aggregate index, a 90 day government bond yield, a 10 year government bond yield, the log of a stock price index (in real terms, using January 2009 as the base price), and the real effective exchange rate index.\(^6\)

\(^5\)All variables except yields are expressed as log-levels in my estimation.

\(^6\)The 3 month government bond yield is not available for Colombia and I use the short term policy rate in its place.
2.2.3 Construction of the Weight Matrix

The weight matrix aggregates the vector of foreign variables in each VAR-X equation to a weighted sum. This permits the variables in all other countries to influence the corresponding variables in an individual country’s model without selecting specific countries while omitting others. The weight matrix for country $i$ reflects the relative importance of foreign economic developments on domestic conditions contributed by country $j$.

I use one weight matrix in my specification. This matrix is constructed using annual bilateral trade data from the IMF Direction of Trade Statistics. My main specification uses an average of the data from 2008 to 2014.\footnote{As I am interested in a monetary policy shock, it is important to note that there is the possibility my results are being driven by the bilateral trade flows for each country. To control for this, I include a set of estimations of the GVAR with pre-crisis trade weights as a robustness check, which span January 2000 to December 2006.}

2.2.4 Identification Strategy

Identification of shocks within a GVAR framework is complicated by the large dimension of the global model. The requirements for identification of a GVAR are the same as in any VAR model; identification needs $k(k - 1)/2$ restrictions.\footnote{See Bernanke (1986), Blanchard and Watson (1986), and Sims (1986) for contemporaneous restrictions on the variance/covariance matrix. For long run restrictions, see Blanchard and Quah (1989), Clarida and Gali (1994), and for sign restrictions, see Uhlig (2005), Mountford and Uhlig (2009), Arias, Rubio-Ramirez, Waggoner, and Zha (2018).} While this number of restrictions is usually feasible for a small number of countries, Chudik and Pesaran (2016) discuss the difficulties in imposing them in a global framework, in that justification of such a large number of identifying restrictions is not provided in the existing open economy macro literature. The extant literature only focuses on distinguishing between types of shocks, without providing insight regarding the country-specific origins required to identify all shocks within the GVAR model.
Dees et al. (2007) and Chen et al. (2012) suggest a Cholesky decomposition for each country, with an additional assumption that the United States economy affects but does not contemporaneously respond to developments in other countries. This is equivalent to placing the United States VAR-X model as the first country block in the GVAR. While a Cholesky decomposition is plausible for each country, a full ordering is implausible given the high dimensionality of the model.

Other methods of identification would include \textit{a priori} restrictions on the contemporaneous variance/covariance matrix of shocks, long run restrictions on the impulse responses, or by sign restrictions, but all are complicated by cross-country interactions and the high dimensionality of the model.\(^9\) Pesaran et al. (2004), Pesaran and Smith (2006), and Dees et al. (2007) adopt the generalized impulse response function (GIRF) to overcome the identification problems associated with the large dimensionality of the GVAR. The advantage of the GIRF is that it is invariant to the ordering of the variables in the VAR. Rather than using a Cholesky decomposition to orthogonalize the shocks in the model, Pesaran and Shin (1997) employ a shock to the \(j\)th element of the VAR and integrate out the effects of other shocks using the historically observed distribution of the residuals. Unfortunately, the GIRF falls short of practical use because it does not identify shocks via \textit{a priori} economic theory, and thus are difficult to interpret in a meaningful economic context.

The implementation of sign restrictions is a viable alternative to other forms of identification in a GVAR\(^10\), however full identification is cumbersome and subject

\(^9\)See Bernanke (1986), Blanchard and Watson (1986), and Sims (1986) for contemporaneous restrictions on the variance/covariance matrix. For long run restrictions, see Blanchard and Quah (1989), Clarida and Gali (1994), and for sign restrictions, see Uhlig (2005), Mountford and Uhlig (2009), Arias, Rubio-Ramirez, Waggoner, and Zha (2014).

\(^10\)Pesaran (2004) suggests a generalized impulse response function, however it does not employ and \textit{a priori} economic theory, while Dees et al. (2007) and Chen et al. (2012) suggest a Cholesky decomposition for each country, with an additional assumption that the United States economy affects but does not contemporaneously respond to developments in other countries.
to the same dimensionality issues of other identification methods. Fortunately, I am
only interested in a United States monetary policy shock while remaining agnostic
about the sources of any other innovations. As such, partial identification via sign
restrictions may overcome the issues associated with the high dimensionality of the
model.

Following Uhlig (2005), Mountford and Uhlig (2009), and Arias, Rubio-Ramirez,
Waggoner, and Zha (2018), I employ a combination of sign and zero restrictions to
identify a QE shock originating in the United States. To implement the sign restric-
tions, I first begin with the reduced-form GVAR model given in Equation 2.5

\[
y_t = c + \sum_{\ell=1}^{p} A_{\ell} y_{t-\ell} + u_t,
\]

from which I can recover the structural form

\[
A_0 y_t = A_0 c + \sum_{\ell=1}^{p} A_0 A_{\ell} y_{t-\ell} + u_t^*,
\]

where the relationship between the reduced and structural coefficient matrices is given
by

\[
A_\ell^* = A_0^{-1} A_{\ell}, \tag{2.10}
\]

and the structural residuals are

\[
u_t^* = A_0^{-1} u_t, \tag{2.11}
\]

or, equivalently,

\[
u_t = A_0 u_t^*. \tag{2.12}
\]
The variance/covariance matrix of the structural error term $\mathbf{u}_t^*$ is normalized such that

$$
\mathbb{E}\left(\mathbf{u}_t^* \mathbf{u}_t^{*-}\right) = \Sigma_{\mathbf{u}^*} = I_k.
$$

Identification of the structural model imposes sign restrictions on the elements of the matrix $\mathbf{A}_0^{-1}$, rather than $\mathbf{A}_0$. Uhlig’s (2005) algorithm partially identifies elements of only one column of $\mathbf{A}_0$ to represent the responses of the model’s corresponding variable to a shock of particular interest. The Bayesian approach to identification with sign restrictions uses a non-informative inverted Normal-Wishart prior to avoid potential bias from priors that are set too tightly to allow the data to speak for itself. The posterior is generated via a Markov Chain Monte Carlo (MCMC) method. First, the orthogonal innovations of the VAR are extracted using a lower-triangular Cholesky decomposition and the resulting impulse response functions are computed.\(^{11}\) A $(k \times 1)$ orthogonal impulse vector $\mathbf{\alpha}$ is randomly drawn with replacement from the unit sphere such that

$$
\mathbf{\alpha} = \mathbf{A}_0^{-1} \mathbf{a},
$$

where

$$
\Sigma_{\mathbf{u}} = \mathbf{A}_0 \Sigma_{\mathbf{u}} \mathbf{A}_0' = \mathbf{A}_0 \mathbf{I}_k \mathbf{A}_0' = \mathbf{A}_0 \mathbf{A}_0'
$$

is a matrix decomposition of $\Sigma_{\mathbf{u}}$, and $\mathbf{a}$ is a $k$-dimensional unit vector. The vector $\mathbf{\alpha}$ is multiplied by the impulse responses computed from the Cholesky decomposition of the residuals. If the structural impulse responses match the imposed sign restrictions,$^{11}$ the Cholesky decomposition serves only as a method of orthogonalization and is not used to identify shocks.
the draw is kept. If not, the draw is discarded and the process repeats until the number of accepted draws or maximum iterations is reached.

In the United States, QE is financed by the creation of excess reserves. Thus, I simulate a QE shock by imposing a positive sign restriction on the narrow money index, that I require to hold for a restriction horizon of six months. Because QE was designed to prevent threats of deflation while maintaining the Fed’s inflation target, I also impose a restriction that the price level not decrease for the duration of the six month horizon. As expansionary monetary policy shocks lead to reductions in long term interest rates and currency devaluation, I require that long term rates and the exchange rate decrease.\footnote{See Schenkelberg and Watzka (2013) and Weale and Wieladek (2016) for additional justification of these restrictions.} Finally, I impose zero contemporaneous impact restrictions on the responses of industrial production and consumer prices, to reflect the delays in the real economy to react to monetary policy surprises. The responses of the other United States variables remain totally unconstrained. Finally, because output and prices cannot immediately respond to a monetary policy surprise, I impose zero contemporaneous impact restrictions on the responses of industrial production and the price level.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Industrial Production</th>
<th>Price Level</th>
<th>Narrow Money Rate</th>
<th>Long Rate</th>
<th>Short Rate</th>
<th>Equity Prices</th>
<th>Exchange Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>QE Shock Domestic</td>
<td>Impact</td>
<td>0</td>
<td>0</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Sign</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>QE Shock Foreign</td>
<td>Impact</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Sign</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 2.2: Identification of a Monetary Policy Shock
I place positive sign restrictions on the responses of the real exchange rate in all foreign countries. A QE shock is a surprise for both output markets and foreign central banks, therefore I place zero restrictions on output, the price level, and the narrow monetary aggregate measure. All of the sign restrictions are imposed for a period of six months. Table 2.2 presents the sign and zero restrictions for my specification.

While this approach is simplified relative to full identification, it does not rule out the existence of other orthogonal innovations with the same pattern as the shock of interest. According to Fry and Pagan (2011) the “multiple models problem” can imply ambiguity in proper identification of the shock of interest. Therefore, Fry and Pagan (2011), Schenkelberg and Watzka (2013), and Weale and Wieladek (2016) discuss the benefits of imposing additional sign restrictions to further ensure proper identification of shocks as a means to address the multiple models problem. The imposition of sign restrictions in a global framework requires additional restrictions to distinguish between United States QE shocks, and other innovations of foreign origin. I also impose additional sign restrictions as a robustness check. For statistical inference, I present 1,000 successful draws of the MCMC process.

---

13 I vary the identifying restrictions as a robustness check, in which foreign yields are required to decrease following a QE shock.

14 Uhlig (2005) and Schenkelberg and Watzka (2013) suggest a degree of arbitrariness in the selection of the restriction horizon. I vary the restriction horizon using one, three, nine, and twelve months as a robustness check.

15 While convention in the sign restrictions literature is to report 1,000 successful MCMC draws, the use of sign restrictions in a GVAR imposes a considerable computing cost with a much larger impact multiplier matrix ($\mathbf{B}_0^{-1}$); Chudik and Fratzscher (2011), Georgiadis (2016), and Anaya, Hachula, and Offermans (2016) report 500 successful draws.
2.3 Results

I report the individual responses of United States variables and the unweighted averages of AEs and EMEs in Figure 2.3. I scale all responses to a 1% increase in the United States narrow money index. Tables 2.3 and 2.4 present the maximum individual responses of AE and EME countries. The impulse responses for the United States are presented in Figure 5, AE responses for individual countries are presented in Figures 6-12, and EME responses are in Figures 13-19 in the appendix.

2.3.1 Impulse Response Analysis

I find both United States industrial production and consumer prices increase in response to a QE shock. The maximum values for industrial production and prices are 1.25% and 2.25% deviations after impact. There are reductions in long term yields by 2 basis points and short term yields by 1.25 basis points. A QE shock also increases equity prices by 1.9%.\(^{16}\)

Federal Reserve asset purchases appear to spill over to foreign economies through interest and foreign exchange rates. Monetary policy expansion in the United States is likely to be followed by lower long term rates in AEs and short term rates in EMEs to maintain domestic stability, cut interest rate spreads, and reduce exchange market appreciation pressures. The spillover of QE places upward pressure on the foreign currency. However, I find that both AEs and EMEs respond with expansionary monetary policy of their own, as evidence by the downward pressure on yields.

Foreign monetary policy responses to a United States QE shock imply long term yield reductions by 4.5 basis points in AEs and 2 basis points in EMEs. Long term rates are likely to be influenced through QE spillovers as a result of freer cap-

\(^{16}\)To compare my results to other works, Weale and Wieladek (2016) find a 0.58% increase in output and a 0.62% increase in consumer prices.
ital flows, which allow higher interconnection between global markets. These yield reductions induce agents to find alternative investments in other markets, increasing demand for bonds in EMEs, while lowering their respective yields. Thus, when the United States aims to reduce domestic long term yields with QE, it is followed by lower interest rates elsewhere. The negative responses in yields and positive responses in monetary aggregates imply foreign central banks follow in kind with the Federal Reserve’s monetary policy measures, thus offsetting negative spillover effects. These foreign monetary responses lead to positive co-movements between United States and foreign macro variables, consistent with a prosper-thy-neighbor effect after a QE shock. My results are consistent with those of Bluedorn and Bowdler (2011), Abdelfaki and Feki (2012), Georgiadis (2016), and Anaya, Hachula, and Offermanns (2016).

Exchange rate responses in EMEs to a United States QE shock are larger.
Table 2.3: Advanced Economy Maximum Responses

<table>
<thead>
<tr>
<th></th>
<th>Industrial Production (% Dev.)</th>
<th>Consumer Prices (% Dev.)</th>
<th>Narrow Money (% Dev.)</th>
<th>Long Rate (Bps)</th>
<th>Short Rate (Bps)</th>
<th>Equity Prices (% Dev.)</th>
<th>Exchange Rate (% Dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.6</td>
<td>0.4</td>
<td>0.5</td>
<td>-4.0</td>
<td>-1.0</td>
<td>0.2</td>
<td>0.5</td>
</tr>
<tr>
<td>Canada</td>
<td>1.1</td>
<td>0.7</td>
<td>2.1</td>
<td>-5.0</td>
<td>-2.1</td>
<td>1.2</td>
<td>1.5</td>
</tr>
<tr>
<td>Denmark</td>
<td>3.0</td>
<td>1.8</td>
<td>2.1</td>
<td>-3.0</td>
<td>-5.0</td>
<td>1.4</td>
<td>1.0</td>
</tr>
<tr>
<td>Eurozone</td>
<td>0.7</td>
<td>1.0</td>
<td>0.8</td>
<td>-3.5</td>
<td>-3.0</td>
<td>0.9</td>
<td>2.8</td>
</tr>
<tr>
<td>Iceland</td>
<td>2.0</td>
<td>1.0</td>
<td>1.8</td>
<td>-1.5</td>
<td>-3.5</td>
<td>2.1</td>
<td>4.0</td>
</tr>
<tr>
<td>Israel</td>
<td>2.0</td>
<td>2.0</td>
<td>2.5</td>
<td>-2.8</td>
<td>-4.0</td>
<td>2.2</td>
<td>1.5</td>
</tr>
<tr>
<td>Japan</td>
<td>2.5</td>
<td>1.0</td>
<td>1.8</td>
<td>-6.0</td>
<td>-6.0</td>
<td>1.8</td>
<td>1.8</td>
</tr>
<tr>
<td>New Zealand</td>
<td>1.0</td>
<td>1.7</td>
<td>1.3</td>
<td>-4.5</td>
<td>-3.0</td>
<td>2.5</td>
<td>2.5</td>
</tr>
<tr>
<td>Norway</td>
<td>0.7</td>
<td>1.1</td>
<td>1.1</td>
<td>-5.9</td>
<td>-1.0</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>Sweden</td>
<td>0.3</td>
<td>1.3</td>
<td>0.2</td>
<td>-4.0</td>
<td>-1.0</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>Switzerland</td>
<td>0.4</td>
<td>0.4</td>
<td>0.8</td>
<td>-0.3</td>
<td>-0.3</td>
<td>0.4</td>
<td>0.4</td>
</tr>
<tr>
<td>U.K.</td>
<td>1.3</td>
<td>1.2</td>
<td>1.5</td>
<td>-0.6</td>
<td>-0.6</td>
<td>1.3</td>
<td>1.3</td>
</tr>
</tbody>
</table>

Note: The maximum responses reported in this table do all occur at the same time, and thus averages from this table will differ from the unweighted mean of impulse responses in Figure 2.3.

than AEs. Referring to Tables 2.3 and 2.4, I find AE exchange rate increases are the largest in the Euro Area, Japan, and the United Kingdom, all with increases above 1%, with remaining AE exchange rates increasing by less than 1%. The largest EME responses are experienced by Hungary (7.3%), Poland (5.0%), Mexico (4.0%), Colombia (3.8%), and Brazil (3.8%). The average maximum exchange rate response after impact in Figure 2.3 is 3% in EMEs and 1% in AEs. This increase in the exchange rate generates risks of capital flight, compelling EMEs to engage in more aggressive monetary policy measures than AEs. The average maximum response of narrow money is 1.5% in EMEs and 1.2% in AEs. Table 2.4 indicates the largest EME narrow money responses for individual countries are in Hungary (2.6%), Chile (2.1%), China (2.0%), Turkey (1.8%), Poland (1.5%), Colombia (1.3%), and Brazil (1.2%). Narrow money responses AEs in Table 2.3 are the largest in Israel (2.5%), Canada (2.1%), Denmark (2.1%), Iceland (1.78%), and Japan (1.8%).

Monetary expansion in both AEs and EMEs lead to an increase in the price
Table 2.4: Emerging Market Economy Maximum Responses

<table>
<thead>
<tr>
<th></th>
<th>Industrial Production (% Dev.)</th>
<th>Consumer Prices (% Dev.)</th>
<th>Narrow Money (% Dev.)</th>
<th>Long Rate (Bps)</th>
<th>Short Rate (Bps)</th>
<th>Equity Prices (% Dev.)</th>
<th>Exchange Rate (% Dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brazil</td>
<td>1.4</td>
<td>1.6</td>
<td>1.2</td>
<td>-5.0</td>
<td>-13.0</td>
<td>1.8</td>
<td>3.8</td>
</tr>
<tr>
<td>Chile</td>
<td>1.3</td>
<td>2.0</td>
<td>2.1</td>
<td>-1.3</td>
<td>-16.0</td>
<td>0.9</td>
<td>3.1</td>
</tr>
<tr>
<td>China</td>
<td>1.0</td>
<td>0.8</td>
<td>0.9</td>
<td>-5.7</td>
<td>-7.0</td>
<td>0.4</td>
<td>1.5</td>
</tr>
<tr>
<td>Colombia</td>
<td>1.0</td>
<td>1.3</td>
<td>1.4</td>
<td>-14.0</td>
<td>-6.7</td>
<td>2.8</td>
<td>3.8</td>
</tr>
<tr>
<td>Czech Rep.</td>
<td>0.2</td>
<td>0.1</td>
<td>0.2</td>
<td>-3.0</td>
<td>-1.0</td>
<td>0.2</td>
<td>2.5</td>
</tr>
<tr>
<td>Hungary</td>
<td>1.0</td>
<td>0.3</td>
<td>2.6</td>
<td>-5.0</td>
<td>-24.0</td>
<td>2.0</td>
<td>7.3</td>
</tr>
<tr>
<td>India</td>
<td>1.0</td>
<td>1.0</td>
<td>0.6</td>
<td>-7.0</td>
<td>-10.0</td>
<td>0.4</td>
<td>2.1</td>
</tr>
<tr>
<td>Mexico</td>
<td>1.2</td>
<td>1.8</td>
<td>1.1</td>
<td>-1.1</td>
<td>-7.5</td>
<td>0.6</td>
<td>4.0</td>
</tr>
<tr>
<td>Poland</td>
<td>1.2</td>
<td>1.1</td>
<td>1.5</td>
<td>-3.5</td>
<td>-5.0</td>
<td>0.5</td>
<td>5.0</td>
</tr>
<tr>
<td>Russia</td>
<td>0.2</td>
<td>0.1</td>
<td>0.2</td>
<td>-1.1</td>
<td>-2.5</td>
<td>0.3</td>
<td>1.1</td>
</tr>
<tr>
<td>South Korea</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>-0.5</td>
<td>-0.3</td>
<td>0.2</td>
<td>1.6</td>
</tr>
<tr>
<td>Turkey</td>
<td>1.4</td>
<td>2.0</td>
<td>1.8</td>
<td>-13.0</td>
<td>-18</td>
<td>0.8</td>
<td>2.2</td>
</tr>
</tbody>
</table>

Note: The maximum responses reported in this table do all occur at the same time, and thus averages from this table will differ from the unweighted mean of impulse responses in Figure 2.3.

level, however the lagged response is induced by construction of the identifying restrictions. As AEs are more likely to have monetary policy rules than EMEs, policy responses by AEs are less aggressive. The maximum average impact of consumer prices is 1% in AEs and 1.75% in EMEs. These results are consistent with Chudik and Fratzscher (2011), who find larger responses in consumer prices in EMEs. The average responses of industrial production in Figure 2.3 are larger in AEs than EMEs. AEs experience a 1.6% increase in production while EME output increases by 1%. These findings are also consistent with Chudik and Fratzscher (2011). Table 2.3 indicates the largest output responses for AEs are in Denmark (3.0%), Japan (2.5%), Israel (2.0%), Iceland (2.0%), and the United Kingdom (1.3%).

The EMEs in Table 2.4 with the largest consumer price responses to a QE shock are Chile (2.0%), Turkey (2.0%), Mexico (1.8%), Brazil (1.6%), and Colombia (1.3%), and China (0.8%). Each of these economies have increases in industrial production above 1%. 
2.3.2 The Role of Foreign Economic Characteristics in Monetary Policy Responses to QE

I regroup the economies by characteristics of their monetary authority regimes. I present and discuss the results of country groupings by inflation targeting and foreign exchange rate regimes. I report the unweighted averages in all of my impulse response functions in this subsection.

2.3.2.1 Inflation Targeting Regimes

First, I group economies by central banks with inflation targeting or other monetary aggregate rules. Economies with inflation targeting regimes can provide a more preferable habitat for investors. If an economy’s central bank announces and maintains a credible commitment to an inflation target, then investment in that economy will be more attractive than in non-inflation targeting regimes. The countries in my sample are explicit inflation targeters: Australia, Brazil, Canada, Chile, Colombia, the Czech Republic, the Eurozone, Israel, India, Japan, Mexico, New Zealand, Norway, Poland, Turkey, Russia, South Korea, Sweden, and the United Kingdom. All other countries are treated as non-targeters. I refer to the IMF classification of inflation targeting regimes for my sample grouping.

Figure 2.4 presents the impulse responses for regimes separated by inflation targeting policies. The monetary policy responses of inflation targeting banks is significantly less pronounced than non-targeters. Long term yields decrease by 6 basis points for inflation targeting banks and 2 basis points in non targeting regimes. Short term yields fall by 4 basis points for inflation targeters, and 7 basis points for non targeters. Narrow money increases by 0.4% for inflation targeters and 1.4% for non targeters. Following the monetary policy response, consumer prices increase.
Figure 2.4: Inflation Targeting Regimes

Note: The dark purple and orange impulse responses reported are unweighted averages of medians of 1,000 successful MCMC draws for AEs and EMEs.

by 1% in targeting countries, and 1.8% for non targeting countries. As inflation targeting economies generate more stable monetary policy responses, less uncertainty is generated regarding the perceived volatility in prices. This induces investors to alter their asset holdings in favor of inflation targeting economies, leading to larger responses in equity prices. Furthermore, industrial production increases by 1.1% in economies with an inflation target, whereas economies with no inflation targeting policy experience an increase in industrial production of 0.6%.
2.3.2.2 Exchange Rate Regimes

I consider exchange rate characteristics of each economy, motivated by the Mundell-Fleming “trilemma”. If countries let their currency freely float, the trilemma suggests they could have independence from United States monetary policy, shielding themselves against undesirable policy spillovers from QE. Klein and Shambaugh (2015) and Aizenman et al. (2016) provide evidence for this trilemma, however Rey (2013) argues in favor of a dilemma, in which a floating exchange rate regime is not enough to buffer foreign economies against QE shocks.

I separate economies according to their exchange rate policies. I use two groups; floaters and peggers. Ideally, I would separate the sample economies as either floaters or peggers by their stated policy preferences, but the list of de jure and de facto exchange rate regimes is not always similar. Additionally, most of the countries in my sample are considered to be de jure floaters. I refer to the IMF classification of de facto exchange rate regimes for my sample grouping.

The floating economies are Australia, Brazil, Canada, Chile, Colombia, Euro-zone, Hungary, Iceland, India, Israel, Japan, Mexico, New Zealand, Norway, Poland, South Korea, Sweden, Turkey, and the United Kingdom. The peggers are China, the Czech Republic, Denmark, and Switzerland. The list of peggers is composed of primarily soft peggers, however Denmark has a conventional peg.

Figure 2.5 presents the results for the floating and pegged exchange rate groups. The real exchange rate responses give validity to the theoretical predictions that monetary policy spillovers generate stronger appreciation pressures on the exchange rate in floating exchange rate regimes. The response of the real exchange rate is 3% in free floating regimes and 1.4% in pegged exchange rate regimes; results
Figure 2.5: Median Impulse Responses for Floating and Non-Floating Exchange Rate Regimes

Note: The purple and blue impulse responses reported are unweighted averages of medians of 1,000 successful MCMC draws for AEs and EMEs.

that are qualitatively consistent with Hoffmann (2007) and Georgiadis (2016).\textsuperscript{17}

While economies with floating exchange rate regimes should enjoy monetary policy independence from the Federal Reserve, I find they still respond in kind following a QE shock. Floating exchange rate economies experience less mirroring in bond yields than managed exchange rate regimes, however their monetary policy responses are not statistically insignificant, as would be expected if they had complete monetary autonomy. Free floating economies have reductions in long term yields by 2 basis points and short term yields by 4 basis points. In contrast, peggers have long term yield reductions by 6 basis points for long term yields, and 7 basis points for short term yield. Additionally, the maximum impacts in narrow money for floating exchange rate regimes is 0.7%, compared to 0.95% for peggers.

Similar to the inflation targeting economies, central banks that adopt floating

\textsuperscript{17}This reflects the fact that Denmark is the only economy with a conventional peg in the sample.
exchange rate policies generally respond less aggressively than those with pegged exchange rates. Economies that can credibly commit to maintaining a floating exchange rate can guarantee less volatility in the monetary responses to spillovers from foreign markets. While the exchange rate increases by nearly double that of the pegged exchange rate economies, equity prices increase by 0.3% more, and industrial production increases by 1.1% for floaters and 0.6% for peggers. Consumer prices increase by 0.75% for free floaters and 1.1% for managed exchange rate regimes. While I find that economies with free floating exchange rates respond less aggressively than those with pegged exchange rates, my results support the conclusions of Anaya, Hachula, and Offermanns (2016), Passari and Rey (2015), and Rey (2016), who find that a floating exchange rate regime is not sufficient to insulate foreign economies from an unconventional monetary policy shock.
2.3.3 Forecast Error Variance Decomposition

I present the results of the forecast error variance decomposition (FEVD) to investigate the relative contribution of a United States unconventional monetary policy shock to foreign variables. Figure 2.6 presents the FEVDs for the United States and the unweighted averages of the FEVDs for AEs and EMEs. Figures 2.7 and 2.8 present the unweighted averages of the FEVDs for AEs and EMEs. Individual FEVD plots are presented in Appendix B.2.

The United States FEVDs in Figure 2.6 indicate that a QE shock explains 12% of the variance in industrial production, and 12.5% in consumer prices. Furthermore, a QE shock appears to contribute roughly 35% of the explained variance in long term yield upon impact, and 16% for short term yield. This provides more evidence of QE operating through long term yield in the United States. Furthermore, a QE shock explains nearly 12% of the variance in equity prices, and 8% for the real exchange rate.

Figure 2.6 suggests a QE shock contributes substantially more to United States industrial production and consumer prices, while providing little to the explained variance in these variables in foreign economies. A QE shock contributes more to AE output (6.2%) than for EMEs (4%), however the reverse holds for consumer prices. A QE shock contributes 5.2% of the explained variance for AEs in consumer prices and 7.5% for EMEs. This lends additional support for the conclusions of Chen et al. (2012) and Barroso et al. (2015), who find EMEs respond with larger increases in prices than AEs. This is especially true for Latin American economies, who have some of the largest shares of the variance in prices explained by a QE shock.

Despite the small contributions of QE to industrial production and prices in foreign economies, it is perhaps evident of effective foreign monetary policy responses
Figure 2.6: Forecast Error Variance Decomposition

Note: The purple and blue FEVDs are unweighted averages of AEs and EMEs.

to QE. The most substantial contributions of a QE shock in foreign economies are generated through interest rates, equity prices, and the real exchange rate. After impact, 25% of long term yield variance in AEs is explained by QE. In addition, 11.5% of equity price variance in AEs is explained by QE.\textsuperscript{18} QE appears to explain more variance in short term yields in EMEs (16%) than AEs (13.5%). Thus, a QE shock propagates through different interest rate transmission mechanisms in AEs than in EMEs. These findings are supported by those of Chudik and Fratzscher (2011). Furthermore, a QE shock contributes 10.5% of the explained variance in the real exchange rate for AEs, and 12.7% in EMEs.

I also discuss the FEVDs for inflation targeting and floating exchange rate regimes. Figure 2.7 presents the FEVDs for groupings based on inflation targeting policy and Figure 2.8 presents the FEVDs for floating and pegged exchange rate regimes.

\textsuperscript{18}See Vayanos and Vila (2009) and Weale and Wieladek (2016).
regimes. A QE shock contributes more to inflation targeting regimes through exchange rates, yields, equity prices, output, and consumer prices. However, narrow money measures of non inflation targeting economies experience a larger contribution of QE than targeters.

The FEVDs for floating and pegged exchange rate regimes imply a QE shock from the United States explains more variance in narrow money, consumer prices, and long term yields in pegging economies. As UMP spillovers generate pressure on exchange rates, foreign central banks engage in more substantial policy responses, thereby reducing yield while increasing narrow money and consumer prices. The shares of the variance in exchange rates, equity prices, and industrial production, however, are larger for floating exchange rate economies. As foreign banks with floating exchange rate policies respond less to monetary policy spillovers than peggers,
Figure 2.8: Forecast Error Variance Decomposition: Exchange Rate Regime

Note: The pink and dark blue FEVDs are unweighted averages of floating and pegging exchange rate regimes.

it is not surprising that a QE shock explains more variation in floating exchange rate economies.
2.3.4 The Transmission Mechanism of Monetary Policy

I discuss the implications of my results with respect to the transmission mechanisms through which QE may have operated in both the United States and foreign economies. I test for interest rate and exchange rate channels, with emphasis on the presence of the portfolio rebalance channel, which is argued to have been activated as a response to UMP measures.\textsuperscript{19}

The results for the United States imply activation of the portfolio rebalance channel. The reduction in long term yields by 2 basis points in the United States coupled with a maximum response of equity prices by 1% are consistent with the literature, namely Weale and Wieladek (2016). The FEVDs provide additional evidence in favor of the activation of this channel in the United States, in that 35% of the variance in long term rates, and nearly 12% of the variance in equity prices is explained by a QE shock.

In AEs, a large reduction in long term government bond yields by 4.5 basis points coupled with an increase in equity prices by 1.9% provide evidence of portfolio rebalancing channel activation. This is further supported by the FEVDs, in which 25% of the variance in long term yields and 11.5% of the variance in equity prices are explained by a QE shock. I conclude there is an activation of this transmission mechanism for all AEs in my sample with the exceptions of Sweden and Switzerland, who appear to respond more through short term than long term yields. My results regarding activation of the portfolio rebalance channel in foreign economies support the findings of D’Amico and King (2010), Gagnon et al. (2012), and Hamilton and Wu (2012), who conclude it serves as a significant mechanism through which QE affects cross-border capital flows.

\textsuperscript{19}See Weale and Wieladek (2016) and Vayanos and Vila (2009).
Evidence for this channel is less definitive in EMEs, which appear to respond more through short term yield with smaller increases in equity prices. EMEs experience an 8.1 basis point reduction in short term yield, in which 16% of the variance can be explained by a QE shock. A few notable exceptions, however, are Colombia, Poland, and Russia, where long term rates are more responsive following United States QE implementation.

The responses of AEs and EMEs, as indicated previously, imply operation through exchange rate channels. The maximum average responses of AEs in Figure 2.3 are 1% for AEs and 3% for EMEs. Figure 2.6 indicates QE contributes 10.5% of the explained variance in exchange rates for AEs and 12.7% in AEs. Unsurprisingly, there is especially strong evidence to imply activations of this channel are stronger in floating exchange rate economies.
2.3.5 Robustness Checks

I perform multiple robustness checks in this section. The checks discussed in this paper include varying trade weights to confirm the presence of an indirect trade channel operating in my analysis, estimating my GVAR using a pre-financial crisis period of January 2000 to December 2006, running an alternative identification scheme, and finally, estimation with variations in the horizons for which the sign restrictions hold. All of these checks confirm the robustness of my GVAR model to various alterations in the specification.

2.3.5.1 Pre-Crisis Trade Weights

To assess the impacts of a direct or indirect trade channel, I use an alternative trade flow weight matrix for the reduced form GVAR estimation with trade weights averaged over the sample period 2000-2008. This sample period is included because it covers a period during which the Eurozone was on the Euro as their currency. Similar to the approach by Cesa-Bianchi, Pesaran, Rebucci, and Xu (2012), the inclusion of this sample period allows me to ensure the quantitative and qualitative results are robust to different trade weights.

Figure 2.9 presents the impulse responses of the GVAR with different trade weights. The individual impulse responses for this exercise are contained in Appendix B.3. The similarity of the responses with different trade weights suggest there are no substantially different results when altering the weighting schemes. Consistent with Cesa-Bianchi, Pesaran, Rebucci, and Xu (2012), this implies the presence of indirect trade channel operations. Therefore, my results are not driven by any form of trade agreements/flows. My results run counter to the claims by Lavigne et al. (2014), who argues that QE spillovers transmit through trade channels to fuel economic recovery
in EMEs. Thus, it is not likely QE operates through direct trade channels.

2.3.5.2 Pre-Crisis Sample Period

I use a sample period of the pre-financial crisis as a second robustness check, beginning in January 2000 and terminating in December 2006. The pre- and post-crisis periods are compared in Figure 2.10. The individual impulse responses are presented in Appendix B.4.

The qualitative responses for both pre- and post-crisis sample periods are similar, however the magnitudes differ substantially. The responses for the pre-crisis sample period are dampened relative to the post-crisis period, which is consistent with the existing literature. Importantly, I conclude the results for the variables in my specification are insensitive to changes in the sample period.
Figure 2.10: Median Impulse Responses with Pre-Crisis Period

Note: The purple and blue impulse responses reported are unweighted averages of medians of 1,000 successful MCMC draws for AEs and EMEs.

2.3.5.3 Variations in the Identifying Restrictions

To address the possibility of the “multiple models problem” discussed by Fry and Pagan (2011), I impose two different sets of sign restrictions to identify a United States QE shock and its spillovers abroad. It is common in the literature to impose additional sign restrictions beyond the shock of interest.\(^\text{20}\)

In the first set of alternative sign restrictions, as performed by Weale and Wieladek (2016), I impose a negative sign restriction on the response of United States long and short term yields. I also restrict the response of equity prices in the United States to be positive. For the sign restrictions in foreign countries, I require narrow money increase after a United States QE shock. In light of the justifications from Alpanda and Kabaca (2015) on the responses of long term interest rates, I require

\(^\text{20}\)See Weale and Wieladek (2016) and Schenkelberg and Watzka (2013) for the imposition of additional sign restrictions to further identify the shocks of particular interest in the analysis.
Table 2.5: Alternative Identification of a Monetary Policy Shock

<table>
<thead>
<tr>
<th>Variable</th>
<th>Industrial Production</th>
<th>Price Level</th>
<th>Reserve Balances</th>
<th>Long Rate</th>
<th>Short Rate</th>
<th>Equity Prices</th>
<th>Exchange Rate</th>
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<td><strong>QE Shock Domestic II</strong></td>
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<td><strong>QE Shock Foreign II</strong></td>
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</table>

As a second set of alternative identification, I impose fewer restrictions in the foreign responses to a QE shock, similar to those performed by Chudik and Fratzscher (2011) and Anaya, Hachula, and Offermans (2016). I only place zero restrictions on the responses of industrial production, consumer prices, and narrow money, and all other foreign variables remain totally unconstrained. This identification scheme can provide additional evidence regarding the transmission mechanism of QE abroad. By leaving exchange and interest rates unconstrained in the foreign responses, any significant movements in either variable will further support conclusions regarding activation of these channels in QE spillovers. A summary of the sign and zero restrictions is provided in Table 2.5 under “QE Shock Domestic II” and “QE Shock Foreign II”.

21Note that I do not alter the restriction horizon in this particular exercise; the sign restrictions are still imposed for a period of six months.
Figure 2.11 presents the unweighted averages of the impulse responses for AEs and EMEs. There are no qualitative differences between the results generated from this identification scheme relative to the baseline model discussed in the main part of this paper, however a number of noteworthy quantitative differences occur. All of the bond yield responses in both AEs and EMEs are significant. For reference, ten of the AEs and eight of the EMEs showed significance in yield reduction in the original identification scheme.

Despite the slight differences in the number of significant impulse responses under the alternative identification strategy, the evidence still suggests activation of long term interest rate and portfolio rebalance channels in AEs and short term interest rate channels in EMEs. AEs experience an average maximum reduction in long rates by 3 basis points in the alternative identification scheme, compared to 2 basis points with the original sign restrictions. Short rates in AEs are reduced by
a maximum of 2.1 basis points with the original sign restrictions, and 0.5 with the additional restrictions imposed. Long rates in EMEs originally fall by 5 basis points under the original identification, and 1.85 basis points with the alternative set of sign restrictions. Short term yields decrease by 9.2 basis points under the original identification method, and drop by 5 basis points with the additional sign restrictions. Thus, while there are some differences in the magnitudes of the reductions in yield in both AEs and EMEs, the channels of monetary policy remain unaffected.

Additionally, I note a larger response in narrow money in EMEs under the alternative identification scheme, with somewhat smaller responses in consumer prices for both AEs and EMEs. Despite these differences, the responses still suggest that AEs experience larger responses in industrial production than EMEs, and EMEs experience larger responses through consumer prices.

The results of the second identification scheme are presented in Figure 2.12.
The results are qualitatively similar to the baseline and first alternative identification schemes. The responses of the magnitudes of the exchange rate and short/long term interest rates are similar to the previous identification schemes. QE still appears to spill over to foreign economies through exchange and interest rate channels.

2.3.5.4 Variation in the Restriction Horizon

As a final robustness check, I vary the horizon that the sign restriction hold after impact. As discussed by Uhlig (2005), it is difficult to select an appropriate restriction horizon, thus leading to a degree of arbitrariness in the selection of this particular parameter in the estimation procedure.22 I estimate my GVAR with the sign restrictions holding for one, three, nine, and twelve months. Reassuringly, my results are qualitatively insensitive to changes in the restriction horizon.

Quantitatively, differences do not arise until I reach the nine and twelve month restriction horizons. I note that the responses longer restriction horizons imply more significant responses in yields for both AEs and EMEs. The impulse responses in Appendices B.6.5-B.6.8 show significant yield reductions in every economy in my sample. Additionally, the responses of narrow money are much more significant and pronounced than under the original restriction horizon.

Another noteworthy difference arises in the responses of industrial production. The response of industrial production is much larger under the longer restriction horizon. Many economies have responses larger than 1% with the nine month restriction horizon. Despite these quantitative differences, the overall results of my paper and the transmission mechanisms of QE in foreign economies remain unchanged; AEs respond through long term yield, and EMEs respond through short term yield.

22Schenkelberg and Watzka (2013) estimate numerous sign restricted impulse responses in their VAR as a sensitivity test involving variations in the restriction horizon.
2.4 Conclusion

The main objective of this paper is to assess foreign central bank responses to a United States QE shock. I use a GVAR with sign and zero restrictions to identify a QE shock without imposing restrictions on real activity, interest rates, or exchange rates. The advantage of using a GVAR to model international spillover effects is that I can consistently estimate spillovers that capture third party spillovers and feedbacks that would not be possible using a bilateral VAR instead. By using sign and zero restrictions, it is possible to avoid imposing an implausible number of restrictions to ensure identification of a GVAR.

My results, which are shown to be robust to various alterations in the specification and identification setup, indicate that a United States QE shock generates spillovers through exchange rate and interest rate channels, with activation of long term yield channels in AEs and short term yield channels EMEs. Foreign central banks respond to a QE shock through implementation of their own expansionary monetary policy measures, however EMEs respond more aggressively to offset negative spillover effects. The responses in industrial production and prices imply AEs respond more through increases in output, while EMEs respond with higher prices. Ultimately, I find that QE generates positive spillover effects in both AEs and EMEs, with some of the largest EME responses in output in Latin America and Turkey. These results support the existing literature.

I group central banks by inflation targeting and exchange rate regimes. Inflation targeters respond with less pronounced policy measures and experience more stable responses than non-inflation targeting banks. Floating exchange rate economies also respond with less aggressive monetary policy measures to offset potential spillover effects of a QE shock. My results for the exchange rate regime grouping support the
findings of Anaya, Hachula, and Offermanns (2016), Passari and Rey (2015), and Rey (2016) that a flexible exchange rate regime may not be enough to adequately buffer economies against monetary policy spillovers from other countries.

In addition, I shed light on the transmission mechanisms of monetary policy, with activation of exchange rate and interest rate channels in both advanced and emerging market economies. A notable difference, however, is that AEs appear to experience policy activation through long term yields coupled with increases in equity prices, indicating activation of the portfolio rebalance channel. EMEs, on the other hand, appear to operate through short term interest rate channels.

Given the limited availability of data in the GVAR I estimate, a more detailed assessment of the particular transmission mechanisms at work in foreign economies following an unconventional monetary policy shock from the United States is difficult. Other channels may be activated through mitigations of perceived risk, and announcements of monetary policy regarding the expected future path of short term interest rates managed through forward guidance.23 Given issues with availability of relevant data in the countries in my sample, tests for this channel are not possible. A further investigation of this issue, with more focus on this mechanism of monetary transmission is left for future research.

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23Bauer and Rudebush (2014) argue the presence of the signaling channel of monetary policy, in which asset purchase announcements send a clear signal to investors regarding the central bank’s intentions to keep short term interest rates low for longer than previously anticipated.
Bibliography


Chapter 3

Black and White Schooling Differentials: An Empirical Investigation of the Value of Equal Education Opportunities

3.1 Introduction

For more than two centuries, African Americans faced substantial levels of discrimination with whites. Jim Crow laws, which were enacted between the late 19th and early 20th centuries, forced racial segregation between whites and blacks in all public facilities in various (mostly Southern) states across the country. Despite being challenged in 1896 in *Plessy vs. Ferguson*, the Supreme Court upheld the laws as constitutional, conditional on a “separate but equal” doctrine for facilities used by African Americans. Despite the Court’s mandate regarding equitable conditions for both races, this ruling was not followed, especially with regard to public education. During the period of 1890 to 1960, state level per pupil expenditures for black students were 67% of white students. In 1954, the *Brown vs. the Board of Education* Supreme Court decision ruled that Jim Crow laws were unconstitutional, thus mandating the removal of segregation policies in the entire United States Not all states
were cooperative in removing them, given the vague time frame during the Court’s ruling. It was not until the Civil Rights Act of 1964 and the Voting Rights Act of 1965 that these laws were entirely abolished from state legislatures across the country. However, despite the integration of whites and blacks in public facilities, guaranteeing an equal access to education among all races in the United States, the policies enacted under Jim Crow can have lasting implications regarding the economic and educational status of African Americans relative to their white cohorts into future generations.

Figure 3.1 presents the average of log real expenditures per-pupil for white and black students in 17 states that had segregation policies in the United States between 1890 and 1960. The data suggest that black students were allocated as little as 41% of white student funding in 1930, and 51% by 1940. This disparity in state-level allocations of funding for white and black students persisted well into the 1960’s, when segregationist policies were eradicated from the United States. Yet despite the efforts of federal and state governments to integrate schools and bring an end to the Segregation era in the United States, the effects of these differences in funding carried persistent consequences regarding substantial disparities in enrollment and graduation rates between whites and blacks.

With major differentials even in educational outcomes of blacks relative to whites in the present day, it is of key importance to investigate the potential mechanisms through which Segregation era policies affected black families and prevented them from catching up to their white age cohort. Figure 3.2 presents the high school graduation rates of white and black students in the United States between 1972 and 2012. The data show a striking differential among the educational attainment between whites and blacks, although the gap in graduation rates has been closing in recent years. However, the graduation rate for blacks 7 years after Segregation was
finally abolished was 72.5%, while for whites, it was 87%. However, by 1991, when white high school graduation rates crossed the 90% mark, blacks were vastly behind, with a graduation rate of 83%, and it took over two decades for their graduation rates to catch up to the white levels from 1991.

These data provide a motivation for the investigation into the differences between white and black education, namely the unequal access to education during the Segregation era in the southern United States. To provide a theoretical explanation for the differentials in access to schooling, the mechanisms through which they propagated, and the ultimate ramifications of Segregation era policies, Tamura, Simon, and Murphy (2016) develop a theoretical framework that documents, explains, and computes the welfare costs of discrimination in black schooling between 1820 and 2000. The model uses a dynamic, dynastic framework of fertility and school choice with quantity and quality dimensions (Becker, Murphy, and Tamura; 1990, Murphy,
Simon, and Tamura; 2008, and Tamura, Simon, and Murphy; 2016). The theoretical framework provides a measure of the price of schooling by race as a parameter outside the model, and shows the consequences and welfare costs between whites and blacks. A key feature of the model is that it allows human capital to accumulate from one generation to the next, and is used to produce the following generation’s human capital stock. Because parents’ human capital stock is used to produce the next generation’s human capital, families with lower parental human capital are less efficient in producing child human capital (Tamura, Simon, and Murphy; 2016). Therefore, despite the removal of discriminatory barriers to equal access to education, the policy ramifications can persist for decades after.

Our paper presents a newly constructed data set on black and white schooling expenditures per pupil for 16 states that operated under segregation between the years 1890 and 1960. The data were gathered by accessing state archival data and Margo’s *Race and Schooling in the South, 1880-1950: An Economic History.*
Through the introduction of this novel data set, we can empirically test the values of key educational efficiency parameters generated in the model presented by Tamura, Simon, and Murphy (2016). We find statistically significant results in favor of the predicted values of the model.\footnote{Earnings data for 1890 to 1930 were not available. Therefore, to accurately fit time series data to values parametrized within the model, we first construct an estimate of average earnings for both whites and blacks by state and year for the years 1890-1930 using earnings data from 1940. We fit the model using decadal data for 16 of the 18 states that engaged in segregation during the time period in our sample (Data for Kentucky and West Virginia were not available for the sample period of interest).}

The results of this paper present a number of important policy implications. First, the model generated values appear to fit closely with the data, providing empirical support that black students faced higher schooling costs than their white student counterparts. Second, as the model presented by Tamura, Simon, and Murphy (2016) includes a law of motion for human capital spillovers across generations within households, the removal of discriminatory barriers in the 1960’s do not provide immediate educational equity across white and African Americans, however parameters within the model allow for convergence in these variables over time, as can be evidenced by the data regarding high school graduation rates between both races. These policy implications suggest that because blacks were consistently discriminated against for nearly two centuries, requiring more time to equalize human capital than it does to achieve convergence in the price and years of schooling.

The rest of this paper is as follows: Section 3.2 provides a discussion of the theoretical model employed in this paper, as well as an explanation of the key parameters of interest in the model. Section 3.3 presents the data construction used to empirically test the model, Section 3.4 provides the results of the empirical tests of the model, Section 3.5 provides a number of robustness checks, and Section 3.6 concludes.
3.2 Generating a Measure of Efficiency of Schooling

Unequal access to schooling was arguably the most important manifestation of racial discrimination against blacks in the US after the end of slavery (Margo; 1990, Canaday and Tamura; 2009). Tamura, Simon, and Murphy (2016) develop a dynamic, dynastic human capital accumulation model to provide a theory-based quantitative measure of the cost to educate a child. The model fits the differential schooling attainment of blacks, arising from differential fertility and discriminatory education provision.

3.2.1 Model Discussion

The model by Tamura, Simon, and Murphy (2016) matches time series of fertility and years of schooling to produce expenditures per pupil for white and black students via the cost of schooling. We first provide a brief discussion of the setup of the model and then discuss the derivation of the key parameters used in describing the unequal access to schooling among black and white students during Segregation in the United States.

3.2.1.1 Preferences

A parent of race $R$ belonging to cohort $t$ and living in state $i$ chooses consumption $c_{i,R,t}$, gross fertility $x_{i,R,t}$, living space per child $S_{i,R,t}$, and human capital investment per child $h_{i,R,t+1}$ in order to maximize the objective function
\[
\alpha \left( c_{i,R,t}^{\psi} s_{i,R,t}^{1-\psi} \right)^\varphi \left[ (1 - \delta_{i,R,t}) x_{i,R,t} - a \right]^{1-\varphi} + \Lambda h_{i,R,t+1}^\varphi \left( 1 - \frac{\beta_{i,R,t} \delta_{i,R,t}}{[(1 - \delta_{i,R,t}) x_{i,R,t} - a] (1 - \delta_{i,R,t})} \right)
\]

where $\delta_{i,R,t}$ is young adult mortality, and in order to place a lower bound on fertility, the model imposes a restriction that $a \geq 0$. Ideally, one would assume that all individuals have identical preferences, regardless of race or state residence. The preference parameters ($\alpha, \psi, \varphi, a, \Lambda$) are identical across race, state, or birth cohort. Two of these parameters ($a, \Lambda$) are fixed by the other taste and technological parameters, and stationary solution values of schooling and fertility.\(^2\)

The fertility and human capital investment decision is similar to the one in Jones (2001), in which declining mortality induces a demographic transition. Higher human capital investment ($h_{i,R,t+1}$) raises parental utility, but is assumed to increase the disutility of child mortality. The precautionary demand for children reflected by $\beta$ and $\nu_{i,R,t}$ is similar to Kalemli-Ozcan (2002, 2003) and Tamura (2006). Higher mortality $\delta_{i,R,t}$ reduces utility both directly, in the final term, and indirectly by reducing net fertility below the gross fertility $x_{i,R,t}$. Declining mortality reduces gross fertility, and in the limit, the final term disappears as mortality approaches zero. Thus, blacks and whites have similar preferences in the limit. The parameter $\bar{\tau}_{i,R,t}$ is average time spent in school by the children born to parents of generation $t$, and is an external effect of schooling that no parent internalizes. The parameter $\rho_t$ determines the diffusion of human capital spillovers from one generation to the next, and generates the convergence of human capital levels seen in the data. The model further requires that $\rho_t \geq 0$, which implies that as long as schooling in the state is positive, children can take some advantage of the state of the art human capital in existence. The more education society provides on average to its children, the more it can benefit from

\(^2\)For a more detailed exposition of the model, see Tamura, Simon, and Murphy (2016).
learning as opposed to innovating and discovering by itself.

### 3.2.2 Technology of Human Capital Accumulation

The law of motion for human capital is given by

\[ h_{i,R,t+1} = A\bar{h}_t^{\rho_t} h_{i,R,t}^{1-\rho_t} \tau_{i,R,t}^{\rho_t} \]  

(3.2)

and

\[ \rho_t = \min \left\{ .5, \frac{.5\bar{\tau}_{i,R,t}}{0.38125} \right\} \]  

(3.3)

Parents choose the amount of time to devote to educating their child, \( \tau_{i,R,t} \), which is identified with years of schooling. The productivity of this time is positively related to the unobserved existing stock of their human capital, \( h_{i,R,t} \), and the unobserved frontier level of human capital in the economy, \( \bar{h}_t \). The term \( \bar{h}_t \) introduces a human capital spillover. Parents are assumed to have perfect foresight regarding the effect of \( \tau_{i,R,t} \) on \( \rho_{i,R,t} \), but ignore the effect of their choice on \( \tau_{i,R,t} \), \( \rho_{i,R,t} \), and \( \bar{h}_t \).

Tamura (2006) assigns each period a life 40 years, thus 40\( \tau_t \) is equal to the average number of years of schooling observed for a representative member of the birth cohort \( t + 1 \), born to parents of generation \( t \). To illustrate this particular mechanism, suppose there are identical durations of schooling equal to 12 years in two states that start out with different (initial) unobserved human capital stocks \( h_{i,t} \). Thus, \( \tau_t = \frac{12}{40} = 0.30 \), \( \rho_t = 0.3934 \), \( 1 - \rho_t = 0.6066 \). The ratio of human capital in the two states after 1 period is

\[ \frac{h_{i,t+1}}{h_{j,t+1}} = \left( \frac{h_{i,t}}{h_{j,t}} \right)^{0.6066} \]  

(3.4)
As income is proportional to human capital, this implies a rate of income convergence of $1 - 0.6066^{0.025} = 1.24\%$ per year. At 15.25 years of schooling, $\tau_t = 0.38125$, $\rho_t = 0.50$, and convergence is 1.7\% per year. Finally, at 8 years of schooling, $\tau_t = 0.20$, $\rho_t = 0.2623$, and convergence is only 0.76\% per year. A maximum value of $\rho_t$ of 0.50 is consistent with the rate of income convergence of 1-2\% per year observed in the data.\(^3\)

### 3.2.2.1 The Parental Budget Constraint

The parent’s budget constraint requires that total consumption be equal to income. The budget constraint is given by

$$pc_{i,R,t} + r_{i,R,t}x_{i,R,t}S_{i,R,t} = h_{i,R,t} [1 - x_{i,R,t} (\theta + \kappa_{i,R,t}\tau_{i,R,t})],$$  

where $p$ is the price of consumption, child rearing takes a fixed proportion of time per child, $\theta$, and $r_{i,R,t}$ is the unit price of living space per child $S_{i,R,t}$, included to capture the Baby Boom. Parents divide their time between the labor market and raising children.

### 3.2.2.2 Efficiency of Teaching Time: $\kappa_t$

Unequal access to schooling is an important manifestation of racial discrimination against blacks in the United States after the abolition of slavery at the end of the Civil War (Margo; 1990, and Canaday and Tamura; 2009).\(^4\) An assumption

---

\(^3\)The parametric form given and the magnitudes chosen for $\rho_t$ are largely consistent with the literature on the intergenerational elasticity of earnings between parents and their children. The upper rate of convergence, 1.7\% per year, is consistent with the evidence contained in Tamura (1996, 2001), and Barro and Sala-i-Martin (1991 and 1992).

contained within the model is that unequal access to schooling is manifested through
the parameter $\kappa_t$, which governs the (in)efficiency of schooling time. As the total cost
of schooling one’s child is $\kappa_t \tau_t$, higher values of $\kappa_t$ require greater diversion of time
away from the labor market to produce a given level of human capital investment in
children.

For ease of notation in this subsection, and given that decisions made on the
margin are invariant to state and race, we drop the $i$ and $R$ subscripts in the discussion
of the generation of $\kappa_t \tau_t$ in the model for this particular subsection. If we let $E_t$ be
total expenditures on schooling of the next generation, we have

$$E_t = (h_t N_t) x_t \kappa_t \tau_t,$$

where total income is given by $(h_t N_t)$ and the number of children per adult is $x_t$.
Dividing by $x_t$, we derive expenditures per student as

$$e_t = (h_t N_t) \kappa_t \tau_t.$$  \hspace{1cm} (3.7)

Dividing by total income produces the share of output spent on education per student

$$se_t = \kappa_t \tau_t,$$

which produces a measure of the total schooling cost a family faces for their children.
Next, dividing by the model’s predicted length of time in school, $\tau_t$, we can identify
$\kappa_t$,

$$\frac{se_t}{\tau_t} = \kappa_t.$$  \hspace{1cm} (3.8)

This measure, $\kappa_t$ provides a measure of the efficiency of schooling parents face
when making educational decisions for their children. As the marginal cost faced by black families to send their children to school for an additional year was larger than that faced by whites we would expect \( \kappa_t \) to be larger for black families than whites. While one would expect this to be the case, no restrictions requiring \( \kappa_{i,W,t} < \kappa_{i,B,t} \) were placed in the model.

### 3.3 Generating \( \kappa_t \) and \( \kappa_t \tau_t \) from the Data

This section provides a detailed discussion of how the measures of \( (\kappa_{i,R,t}, \tau_{i,R,t}) \) are constructed using observable data. The data are from various sources including state reports of the superintendent of education accessed from various state archives as well as Margo’s *Race and Schooling in the South, 1880-1950: An Economic History*. Population and earnings census data are accessed from the Integrated Public Use Microdata Series (IPUMS).\(^5\)

#### 3.3.1 Population Estimation

##### 3.3.1.1 Population Over Age 4 Not in School

To generate the population of 5 years and over not enrolled in school, we take enrollment figures for white and black students, and using the age cohort data provided by IPUMS. Let \( \text{er}_{i,R,t} \) be the elementary school enrollment rate for the relevant aged birth cohort (5-13) in the population, we compute a dis-enrollment rate by computing

\[
\text{Elementary (Not Enrolled)}_{i,R,t} = (1 - \text{er}_{i,R,t}), \quad (3.10)
\]

\(^5\)A full description of the data sources are provided in Appendix C.
and if we let $sr_{i,R,t}$ be the secondary school enrollment rate for the cohort aged 14-17, we compute the rate of those not enrolled in a similar fashion, yielding

$$\text{Secondary (Not Enrolled)}_{i,R,t} = (1 - sr_{i,R,t}). \quad (3.11)$$

Finally, if we let $hr_{i,R,t}$ be the higher education enrollment rates for the population aged 18-24, the rate of those not enrolled would be computed as

$$\text{Higher Education (Not Enrolled)}_{i,R,t} = (1 - hr_{i,R,t}). \quad (3.12)$$

We take these age-relevant unenrolled rates and multiply them by the age relevant populations for both blacks and whites separately to derive the population aged 5 and over not enrolled in school ($P5N_{i,R,t}$). This yields

$$P5N_{i,R,t} = (1 - er_{i,R,t}) \times P0513_{i,R,t} + (1 - sr_{i,R,t}) \times P1417_{i,R,t} + (1 - hr_{i,R,t}) \times P1824_{i,R,t}.$$ \quad (3.13)

### 3.3.2 Generating Average Earnings

While the computation of $(\kappa_{i,R,t}^\tau_{i,R,t})^{\text{data}}$ and $\kappa_{i,R,t}^{\text{data}}$ requires a measure of earnings for black and white households, the data needed to calculate incomes for families by race exists for the years between 1940 and 1960, however no such data exist prior to 1940. Therefore, we develop a method in which we can employ wage data from 1940 to estimate earnings for both races between 1890 and 1930.

Let $Y_{i,R,t}^{\text{data}}$ be observed nominal earnings for households in state $i$ of race $R$ at time $t$. As the data for 1940, 1950, and 1960 are provided IPUMS, these years do not necessitate any additional computation. Years prior to 1940 require imputations
in order to create nominal earnings. We assume that workers get 66% of output and that white and black households face the same price level.

To generate values of $Y_{i,j,R,t}^{data}$ through $Y_{i,j,R,t}^{data}$, where $j$ represents the occupation held by household worker $i$, we use 151 listed occupations that consistently identified between 1890 and 1940 in the IPUMS data.\footnote{Note that since the data from the 1910 Census were lost in a fire, we geometrically interpolate the missing values as required.} We use nominal wages of workers 25 to 64, who worked at least 35 hours per week and 35 weeks per year. The following discussion presents the methods used to compute average earnings for the years 1890-1930. The occupations are listed in Tables 8 through 10 in Appendix C.2.

Let $ypw_{i,t}$ be real output per worker given by Turner, Tamura, and Mulholland (2013). We assume workers get 66% of output, thus we multiply $ypw_{i,t}$ by 0.66. Next, as real output per worker is in 2000 dollars, we convert real output per worker to nominal output per worker ($YPW_{i,t}$). In 1940, we observe the nominal output per worker and wage earnings for each state in our analysis. We take the occupational earnings from 1940 and generate a ratio of average nominal earnings to nominal output per worker in 1940, yielding

$$\text{Ratio}_{i,j,R,t=1940} = \frac{Y_{i,j,R,t=1940}^{\text{data}}}{YPW_{i,t=1940}}. \quad (3.14)$$

From this ratio, we can impute the average earnings for prior years 1890-1930 (denoted $t - n$ in Equation 3.15, where $n$ is the number of periods prior to $t=1940$) by multiplying this ratio by nominal output per worker computed for 1890-1930, yielding a measure of a distribution of average earnings for white and black workers across all occupations $j$,

$$Y_{i,j,R,t-n}^{\text{data}} = \frac{Y_{i,j,R,t=1940}^{\text{data}}}{YPW_{i,t=1940}} \times YPW_{i,t-n}. \quad (3.15)$$
We then compute the average nominal earnings by computing the average over all occupations, where the weights are the occupational distribution for whites and blacks in each state in each year of observation, denoted as $Y_{i,j,R,t-n}$. We average across occupation $j$ to provide a measure of average earnings for whites and blacks, weighted by the occupational distribution for each race. The earnings for blacks and whites computed via this method for each state are presented in Appendix C.4.

If we multiply average nominal earnings $Y_{i,R,t-n}$ by the size of the labor force for each race (denoted $N_{i,R,t}$), we produce

$$Y_{i,R,t}^{\text{Total}} = Y_{i,R,t} N_{i,R,t}, \tag{3.16}$$

which provides a measure of total earnings across each race in the sample period.

### 3.3.3 Generating $\kappa_{i,t} T_{i,t}$ from the Data

From Equation 3.8, we can develop a way to empirically test the model by deriving an estimate of $\kappa_{i,R,t} T_{i,R,t}$ from the data if we take the share of total earnings by race spent on education, divide by the number of students, and multiply it by the population aged 5 and above not enrolled in school. This measure is given by

$$se_{i,R,t} = \frac{[\text{Total Education Expenditures}]_{i,R,t}}{Y_{i,R,t}} \frac{[\text{P5N}]_{i,R,t}}{[\text{Student Population}]_{i,R,t}}, \tag{3.17}$$

where Total Education Expenditures divided by the Student Population in Equation 3.17 is per-pupil expenditures. Equation 3.17 is equal to $\kappa_{i,R,t} T_{i,R,t}$:

$$se_{i,R,t} = \kappa_{i,R,t} T_{i,R,t}. \tag{3.18}$$
The next subsection presents the computational methods employed to develop an empirical measure of $\kappa_{i,R,t} \tau_{i,R,t}$ and $\kappa_{i,R,t}$, which can then be tested against the model generated values.

### 3.3.4 Generating $\kappa_t$

As the efficiency parameter of schooling, $\kappa_{i,R,t}$, is of major interest in this paper for empirical tests, we need a measure of $\tau_{i,R,t}$, which is expressed as the share of the expected lifespan of children within their birth cohort in which they are expected to seek education. To acquire this from within the data, we employ the same methods as in Tamura and Simon (2017). We take expected years of schooling divided by a life expectancy of 80 years. Thus,

$$\tau^w_t = \frac{(\text{Expected Schooling})_{i,R,t}}{80}. \quad (3.19)$$

Recall

$$\frac{Se_{i,R,t}}{\tau_{i,R,t}} = \kappa_{i,R,t}, \quad (3.20)$$

thus in dividing $se_{i,R,t}$ derived in the model from Tamura, Simon, and Murphy (2016) by $\tau_{i,R,t}$, we can identify $\kappa_{i,R,t}$ via

$$\frac{se_{i,R,t}}{\tau_{i,R,t}} = \kappa_{i,R,t}. \quad (3.21)$$

By identifying $\kappa_{i,R,t}$ via the above relationship, we can compute a measure of the efficiency of schooling faced by parents in their decision to submit their children to an additional year of education.

Dividing $(\kappa_{i,R,t} \tau_{i,R,t})^{\text{data}}$ by $\tau_{i,R,t}^{\text{data}}$ allows us to identify $\kappa_{i,R,t}^{\text{data}}$, which provides a
measure of the efficiency of schooling for white and black students. This parameter represents the marginal cost parents face when determining the amount of schooling their children will seek. The computed values of $\kappa_{i,R,t}$ are compared to the model generated data in Appendix C.6.
3.4 Empirical Analysis

3.4.1 Tests for $\kappa_{i,t,R}$ and $\tau_{i,t,R}$

In this section, we empirically test the model’s predictions of $\kappa_{i,t,R}$ and $\tau_{i,t,R}$ with the values generated by the data. All data are expressed as natural logs. Table 3.1 presents the summary statistics for the model and data generated $\kappa_{i,t,R}^{\text{data}}$ and $\kappa_{i,t,R}$ in logarithmic form.

As we were unable to collect data regarding per-pupil expenditures for all states in all years, we have only 85 total observations for each race. However Tamura, Simon, and Murphy (2016) provide 143 observations. Therefore, we restrict the sample size of the model-generated values to 85 by removing values of $\kappa_{i,t,R}$ and $\tau_{i,t,R}$ if the observed data for that state and year do not exist. As blacks face higher total time and marginal costs of schooling relative to their white birth cohort, one would expect these values to be higher.

As there were only 85 observations for each race, we combine the data for both whites and blacks, thereby requiring the use of a multidimensional panel data regression, in which there are observations for a representative white and black student within each state in each year. The empirical specification we estimate is a fixed effects multidimensional panel regression model with observations for state $i$ and race $R$ at time $t$, taking the functional form

$$\ln(\kappa_{i,t,R}^{\text{data}}) = c + \beta \ln(\kappa_{i,t,R}^{\text{model}}) + \gamma_i + \epsilon_{i,R,t},$$

where $c$ is a constant, $\gamma_i$ is a vector of state fixed effects, and $\epsilon_{i,R,t}$ is a zero-mean, serially uncorrelated vector of residuals.

We also regress the data generated values of $(\kappa_{i,t,R}^{\text{data}})$ on the model
Table 3.1: Summary Statistics: Model and Data Generated Values for \((\kappa_{i,R,t},\tau_{i,R,t})^{\text{data}}\) and \(\kappa_{i,R,t}\) in Logarithmic Form

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\ln(\kappa_{i,W,t}\tau_{i,W,t})^{\text{model}})</td>
<td>-1.406</td>
<td>0.579</td>
<td>-2.459</td>
<td>-1.667</td>
<td>85</td>
</tr>
<tr>
<td>(\ln(\kappa_{i,B,t}\tau_{i,B,t})^{\text{model}})</td>
<td>-1.542</td>
<td>0.619</td>
<td>-2.821</td>
<td>-0.268</td>
<td>85</td>
</tr>
<tr>
<td>(\ln(\kappa_{i,W,t}\tau_{i,W,t})^{\text{data}})</td>
<td>-3.312</td>
<td>0.756</td>
<td>-5.778</td>
<td>-1.722</td>
<td>85</td>
</tr>
<tr>
<td>(\ln(\kappa_{i,B,t}\tau_{i,B,t})^{\text{data}})</td>
<td>-2.873</td>
<td>0.991</td>
<td>-7.182</td>
<td>-0.885</td>
<td>85</td>
</tr>
<tr>
<td>(\ln(\kappa_{i,W,t})^{\text{model}})</td>
<td>-0.595</td>
<td>0.428</td>
<td>-1.503</td>
<td>0.354</td>
<td>85</td>
</tr>
<tr>
<td>(\ln(\kappa_{i,B,t})^{\text{model}})</td>
<td>-0.343</td>
<td>0.408</td>
<td>-1.294</td>
<td>0.494</td>
<td>85</td>
</tr>
<tr>
<td>(\ln(\kappa_{i,W,t})^{\text{data}})</td>
<td>-1.307</td>
<td>0.744</td>
<td>-3.741</td>
<td>0.256</td>
<td>85</td>
</tr>
<tr>
<td>(\ln(\kappa_{i,B,t})^{\text{data}})</td>
<td>-0.833</td>
<td>0.984</td>
<td>-5.121</td>
<td>1.131</td>
<td>85</td>
</tr>
</tbody>
</table>

generated values using a dummy variable for race to indicate if the student is black, treating whites as the reference group. The panel regression with a race dummy takes the form of

\[
\ln(\kappa_{i,R,t}\tau_{i,R,t})^{\text{data}} = c + \beta \ln(\kappa_{i,R,t}\tau_{i,R,t})^{\text{model}} + \gamma_B + \epsilon_{i,R,t},
\]  

(3.23)

where \(\gamma_B\) is a vector of dummies indicating if the student is black, treating white students as the reference group.

Our third specification utilizes a vector of time and state fixed effects

\[
\ln(\kappa_{i,R,t}\tau_{i,R,t})^{\text{data}} = c + \beta \ln(\kappa_{i,R,t}\tau_{i,R,t})^{\text{model}} + \gamma_i + \gamma_t + \epsilon_{i,R,t},
\]  

(3.24)

where \(\gamma_t\) is a vector of time fixed effects. As the majority of the data were only available from 1890-1960, with too few observations for 1890 to be successfully included in the regression, this year is dropped from the computation, and we treat 1890 as the reference year.

---

7To avoid issues of multicollinearity, we do not include state fixed effects in the race-dummy model.
Finally, our fourth regression specification employs the race dummy and time fixed effects:

$$\ln(\kappa_{i,R,t} \tau_{i,R,t})_{\text{data}} = c + \beta \ln(\kappa_{i,R,t} \tau_{i,R,t})_{\text{model}} + \gamma_R + \gamma_t + \epsilon_{i,R,t}, \quad (3.25)$$

If the model developed by Tamura, Simon, and Murphy (2016) is an accurate descriptor of $\ln(\kappa_{i,R,t} \tau_{i,R,t})_{\text{data}}$, then the estimated coefficient will be expected to be equal to one.

The results for this exercise are presented in Table 3.2. In Model 1, in which we include a vector of state fixed effects, we attain an estimated coefficient of 0.948 on $\ln(\kappa_{i,R,t} \tau_{i,R,t})_{\text{model}}$ with significance at the 1% level. When including race fixed effects, we find an estimated coefficient of 0.898 with significance at the 1% level, and an estimated coefficient of 0.573 with significance at the 1% level for blacks. The inclusion of year and state fixed effects in Model 3 reduces the coefficient on $\ln(\kappa_{i,R,t} \tau_{i,R,t})_{\text{model}}$, with no statistical significance within conventional bounds. However, the individual year fixed effects models show an increase in the estimated coefficients with an increase in time, coupled with increases in statistical significance in more recent years. Finally, the fourth model, which includes year and race fixed effects shows a statistically significant coefficient of 0.286 on $\ln(\kappa_{i,R,t} \tau_{i,R,t})_{\text{model}}$ at the 1% level. The inclusion of a dummy for race shows that there is a significant coefficient on blacks of 0.481 at the 1% level, and the pattern of the magnitude of the coefficients and increases in statistical significance with the time fixed effects are similar to Model 3.

These results indicate that on average, holding all else constant, blacks faced a much higher total cost of attendance than white families. In both models in which a race dummy is included, we find a highly significant and positive effect on the total

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8 Again, we omit the state fixed effects to avoid multicollinearity.
Table 3.2: Regression Results for $\kappa_{i,R,t,\tau_i,R,t}$

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln($\kappa_{i,R,t,\tau_i,R,t}$)_{model}</td>
<td>0.948***</td>
<td>0.898***</td>
<td>0.0101</td>
<td>0.286***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.950)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Race</td>
<td>0.573***</td>
<td></td>
<td></td>
<td>0.481***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
<td>(0.000)</td>
</tr>
<tr>
<td>1900</td>
<td></td>
<td>0.126</td>
<td>0.111</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.445)</td>
<td>(0.524)</td>
<td></td>
</tr>
<tr>
<td>1910</td>
<td>-0.0441</td>
<td></td>
<td>-0.115</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.854)</td>
<td></td>
<td>(0.629)</td>
<td></td>
</tr>
<tr>
<td>1920</td>
<td>0.652**</td>
<td></td>
<td>0.499*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td></td>
<td>(0.052)</td>
<td></td>
</tr>
<tr>
<td>1930</td>
<td>0.742**</td>
<td></td>
<td>0.527*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td></td>
<td>(0.098)</td>
<td></td>
</tr>
<tr>
<td>1940</td>
<td>1.054***</td>
<td></td>
<td>0.762**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td></td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>1950</td>
<td>1.486***</td>
<td></td>
<td>1.126***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>1960</td>
<td>2.075***</td>
<td></td>
<td>1.943***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-1.676***</td>
<td>-2.029***</td>
<td>-3.757***</td>
<td>-3.418***</td>
</tr>
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<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Observations</td>
<td>170</td>
<td>170</td>
<td>170</td>
<td>170</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.382</td>
<td>0.381</td>
<td>0.462</td>
<td>0.533</td>
</tr>
</tbody>
</table>

*p*-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

cost of schooling of blacks relative to whites. These estimates support the model solutions by Tamura, Simon, and Murphy (2016). In addition, these results also confirm the assertions that blacks faced unequal access to education and can provide an empirical justification for the reduced years of schooling blacks attained relative to whites, and thus, reduced accumulation of human capital that followed.
3.4.2 Tests for $\kappa_{i,r,t}$

We test for the fit of the data to the computed values of $\kappa_{i,R,t}$ as well. We include the following fixed effects panel model of the functional form

$$\ln(\kappa_{i,R,t})^{\text{data}} = c + \beta \ln(\kappa_{i,rR,t})^{\text{model}} + \gamma_i + \epsilon_{i,r,t},$$

(3.26)

where $\kappa_{i,r,t}^{\text{data}}$ is the vector of data-generated values of $\kappa_{i,R,t}$ and $\kappa_{i,r,t}^{\text{model}}$ is generated by the model.

We also regress the data generated values of $\kappa_{i,R,t}^{\text{data}}$ on the model generated values using the race dummy in the previous set of specifications. The model takes the functional form of

$$\ln(\kappa_{i,R,t})^{\text{data}} = c + \beta \ln(\kappa_{i,R,t})^{\text{model}} + \gamma_{R} + \epsilon_{i,R,t}.$$  

(3.27)

Our third specification for the estimation of $\kappa_{i,R,t}$ uses a vector of year and state fixed effects of the form

$$\ln(\kappa_{i,R,t})^{\text{data}} = c + \beta \ln(\kappa_{i,R,t})^{\text{model}} + \gamma_i + \gamma_t + \epsilon_{i,R,t},$$

(3.28)

Finally, we include a regression with race and time fixed effects:

$$\ln(\kappa_{i,R,t})^{\text{data}} = c + \beta \ln(\kappa_{i,R,t})^{\text{model}} + \gamma_{R} + \gamma_{t} + \epsilon_{i,R,t},$$

(3.29)

where $\gamma_t$ is a vector of time fixed effects. In addition, should the model accurately describe the data generated values, we expect the estimated coefficients to be one.

The results for the regressions on $\kappa_{i,R,t}^{\text{data}}$ are presented in Table 3.3. The estimated coefficient in the state fixed effects regression is 1.213 with significance at the
<table>
<thead>
<tr>
<th></th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \ln(\kappa_{i,R,t}) )</td>
<td>1.213***</td>
<td>0.997***</td>
<td>0.238</td>
<td>0.146</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.264)</td>
<td>(0.270)</td>
</tr>
<tr>
<td>Race</td>
<td>0.244</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.195)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1900</td>
<td>0.131</td>
<td>0.136</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.455)</td>
<td>(0.444)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1910</td>
<td>-0.0793</td>
<td>-0.0282</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.778)</td>
<td>(0.919)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1920</td>
<td>0.567*</td>
<td>0.636**</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.079)</td>
<td>(0.043)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1930</td>
<td>0.625</td>
<td>0.711*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.126)</td>
<td>(0.071)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1940</td>
<td>0.896**</td>
<td>0.996**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.015)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1950</td>
<td>1.290***</td>
<td>1.396***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1960</td>
<td>1.992***</td>
<td>2.144***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.478***</td>
<td>-0.689***</td>
<td>-1.540***</td>
<td>-1.883***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Observations</td>
<td>170</td>
<td>170</td>
<td>170</td>
<td>170</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.228</td>
<td>0.236</td>
<td>0.218</td>
<td>0.469</td>
</tr>
</tbody>
</table>

*p-values in parentheses
* \( p < 0.10 \), ** \( p < 0.05 \), *** \( p < 0.01 \)

1% level. When including the race dummy, we find an estimate of 0.997 for \( \kappa_{i,R,t} \) with an estimated coefficient of 0.244 on black students with no statistical significance within conventional bounds. While the results for the race dummy model are not statistically significant, they are economically significant, indicating that blacks, on average, holding all else constant, face higher marginal costs of attending an additional year of school than their white counterparts within their birth cohort.

Model 7 presents the estimates for \( \ln(\kappa_{i,R,t}) \) with time and state fixed effects and Model 8 presents the estimates for the model with time fixed effects and
a race dummy. The results in both Models 7 and 8 suggest that the year fixed effects become more significant as the observations become more recent, however race in Model 8 suggests an estimated coefficient of 0.443 for black students with significance at the 1% level. Similar to Model 6, the results in Model 8 results suggest that black students faced higher marginal costs of schooling relative to their white cohort.

The results for the tests on $\kappa_{i,R,t}$ provide us with a number of interesting implications. First, the regression model’s results suggest the model’s values of $\kappa_{i,R,t}$ provide a suitable fit with the data, thus giving evidence of the model’s explanatory power in addressing the unequal access to education between black and white students. Second, the estimated coefficients for $\kappa_{i,R,t}$ in Models 6 and 8 suggest that blacks faced much higher costs of schooling relative to white students, confirming the predictions of Tamura, Simon, and Murphy (2016), explaining the disparity between white and black education and enrollment rates. As per-pupil funding for black students was substantially lower than white funding, suggesting a lower quality of education, along with lower incomes for black families than whites, these results provide substantial evidence in the way of estimating the effects of discrimination against blacks during the Jim Crow era.

The results regarding the tests of $\kappa_{i,R,t} \tau_{i,R,t}$ and $\kappa_{i,R,t}$, support the narrative that as blacks faced higher costs of education relative to whites, black enrollment rates fall and the expected schooling as a fraction of their life expectancy falls substantially relative to white students. Thus, these results provide evidence to support the model by Tamura, Simon, and Murphy (2016) in that human capital accumulates inter-generationally, and that the stock of human capital held by the parents will determine the the spillover of human capital to their progeny via the law of motion of human capital relationship in Equation 3.2. As such, higher costs of educational attainment coupled with lower human capital stocks of black parents lead to implications that
despite the removal of discriminatory barriers faced by blacks to an equitable quality of education to whites more than six decades ago, there is still a persistent differential in educational performance and attainment between the two races.
3.5 Robustness Checks

3.5.1 Tests of $\kappa_{i,t}$ and $\tau_{i,t}$ in Levels

As a robustness check, we include a regression of $\kappa_{i,R,t}$ and $\kappa_{i,R,t}$ in levels, rather than natural logs.

Table 3.4 presents the summary statistics for the model generated values and data for $\kappa_{i,R,t}$ and $\kappa_{i,R,t}$ in levels. It is of note that as the magnitudes of the data in levels differ substantially from logged values in the main section of this paper. As there are substantial differences between the log and level values in the dataset, we do not expect the estimated coefficients to be similar to the regressions in which the variables are expressed in logarithmic form.

Table 3.4: Summary Statistics: Model and Data Generated Values for $\kappa_{i,R,t}$ and $\kappa_{i,R,t}$ in Levels

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>$(\kappa_{i,W,t} \tau_t)^{\text{model}}$</td>
<td>0.288</td>
<td>0.167</td>
<td>0.058</td>
<td>0.846</td>
<td>85</td>
</tr>
<tr>
<td>$(\kappa_{i,B,t} \tau_t)^{\text{model}}$</td>
<td>0.256</td>
<td>0.157</td>
<td>0.059</td>
<td>0.764</td>
<td>85</td>
</tr>
<tr>
<td>$(\kappa_{i,W,t} \tau_t)^{\text{data}}$</td>
<td>0.085</td>
<td>0.043</td>
<td>0.021</td>
<td>0.225</td>
<td>85</td>
</tr>
<tr>
<td>$(\kappa_{i,B,t} \tau_t)^{\text{data}}$</td>
<td>0.040</td>
<td>0.033</td>
<td>0.011</td>
<td>0.201</td>
<td>85</td>
</tr>
<tr>
<td>$\kappa_{i,W,t}^{\text{model}}$</td>
<td>0.603</td>
<td>0.262</td>
<td>0.222</td>
<td>1.424</td>
<td>85</td>
</tr>
<tr>
<td>$\kappa_{i,B,t}^{\text{model}}$</td>
<td>0.769</td>
<td>0.311</td>
<td>0.274</td>
<td>1.638</td>
<td>85</td>
</tr>
<tr>
<td>$\kappa_{i,W,t}^{\text{data}}$</td>
<td>0.186</td>
<td>0.079</td>
<td>0.044</td>
<td>0.405</td>
<td>85</td>
</tr>
<tr>
<td>$\kappa_{i,B,t}^{\text{data}}$</td>
<td>0.134</td>
<td>0.099</td>
<td>0.033</td>
<td>0.449</td>
<td>85</td>
</tr>
</tbody>
</table>

We first test the model for $\kappa_{i,R,t} \tau_{i,R,t}$. The results are presented in Table 3.5. The first two models, in which we include state fixed effects for both, and a race dummy for the second, produce similar quantitative results, with coefficients of 0.189 on $(\kappa_{i,R,t} \tau_{i,R,t})^{\text{model}}$ in the first specification, and 0.155 in the second, with statistical significance at the 1% level in both estimations. The models in which we include time fixed effects produce negative results for the coefficient on $(\kappa_{i,R,t} \tau_{i,R,t})^{\text{model}}$, with
Table 3.5: Regression Results for $\kappa_{i,R,t}\tau_{i,R,t}$ in Levels

<table>
<thead>
<tr>
<th></th>
<th>Model 9</th>
<th>Model 10</th>
<th>Model 11</th>
<th>Model 12</th>
</tr>
</thead>
<tbody>
<tr>
<td>$(\kappa_{i,R,t}\tau_{i,R,t})_{model}$</td>
<td>0.189***</td>
<td>0.155***</td>
<td>-0.0720*</td>
<td>-0.0174</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.100)</td>
<td>(0.522)</td>
</tr>
<tr>
<td>Race</td>
<td>0.0430***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1900</td>
<td>0.000799</td>
<td></td>
<td>-0.000523</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.891)</td>
<td></td>
<td>(0.927)</td>
<td></td>
</tr>
<tr>
<td>1910</td>
<td>-0.00481</td>
<td></td>
<td>-0.00425</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.483)</td>
<td></td>
<td>(0.440)</td>
<td></td>
</tr>
<tr>
<td>1920</td>
<td>0.0258***</td>
<td></td>
<td>0.0233**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td></td>
<td>(0.012)</td>
<td></td>
</tr>
<tr>
<td>1930</td>
<td>0.0322**</td>
<td></td>
<td>0.0267**</td>
<td></td>
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<tr>
<td></td>
<td>(0.013)</td>
<td></td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>1940</td>
<td>0.0572***</td>
<td></td>
<td>0.0467***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td></td>
<td>(0.000)</td>
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<tr>
<td>1950</td>
<td>0.106***</td>
<td></td>
<td>0.0907***</td>
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<tr>
<td></td>
<td>(0.000)</td>
<td></td>
<td>(0.000)</td>
<td></td>
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<tr>
<td>1960</td>
<td>0.224***</td>
<td></td>
<td>0.224***</td>
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<td></td>
<td>(0.000)</td>
<td></td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
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<td>0.0441***</td>
<td>0.0157**</td>
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<td>(0.086)</td>
<td>(0.704)</td>
<td>(0.000)</td>
<td>(0.017)</td>
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<td>Observations</td>
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<td>170</td>
<td>170</td>
<td>170</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.204</td>
<td>0.207</td>
<td>0.521</td>
<td>0.605</td>
</tr>
</tbody>
</table>

$p$-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

statistical significance at the 10% level in only the third specification. The fourth specification, in which we include time fixed effects and a dummy for race does not indicate statistical significance within conventional bounds for the $(\kappa_{i,R,t}\tau_{i,R,t})_{model}$ coefficient, however the coefficient on the race dummy is positive and significant at the 1% level.

We next test the specification for $\kappa_{i,R,t}$ in levels. The results are presented in Table 3.6. The first two specifications suggest coefficients of 0.547 in the state fixed effects model, and 0.368 in the specification in which we include a dummy for
Table 3.6: Regression Results for $\kappa_{i,R,t}$

<table>
<thead>
<tr>
<th></th>
<th>Model 13</th>
<th>Model 14</th>
<th>Model 15</th>
<th>Model 16</th>
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<tr>
<td>$\kappa_{i,R,t}$</td>
<td>0.547***</td>
<td>0.368***</td>
<td>-0.684***</td>
<td>-0.0485</td>
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<td></td>
<td>(0.014)</td>
<td>(0.007)</td>
<td>(0.020)</td>
<td>(0.598)</td>
</tr>
<tr>
<td>Race</td>
<td>0.244***</td>
<td>0.306***</td>
<td>0.306***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
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<tr>
<td>1900</td>
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<td>-0.00831</td>
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<td></td>
<td>(0.331)</td>
<td></td>
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<td>1920</td>
<td>0.230***</td>
<td>0.166**</td>
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<td>(0.012)</td>
<td></td>
<td></td>
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<tr>
<td>1930</td>
<td>0.304**</td>
<td>0.185**</td>
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<tr>
<td></td>
<td>(0.010)</td>
<td>(0.013)</td>
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<tr>
<td>1940</td>
<td>0.518***</td>
<td>0.327***</td>
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<td>(0.000)</td>
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<tr>
<td>1950</td>
<td>0.897***</td>
<td>0.646***</td>
<td></td>
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<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
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</tr>
<tr>
<td>1960</td>
<td>1.560***</td>
<td>1.631***</td>
<td></td>
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<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
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<td>Constant</td>
<td>0.126</td>
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<td>0.608***</td>
<td>0.119**</td>
</tr>
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<td>(0.000)</td>
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<td>170</td>
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<td>170</td>
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<td>$R^2$</td>
<td>0.068</td>
<td>0.135</td>
<td>0.586</td>
<td>0.595</td>
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</table>

*p*-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

race, both of which display statistical significance at the 1% level. In addition, the
estimated race coefficient is 0.244, indicating higher values of $\kappa_{i,R,t}$ for blacks than
whites, providing further evidence to the model by Tamura, Simon, and Murphy
(2016).

Similar to the test for $\kappa_{i,R,t} \tau_{i,R,t}$ in levels, the estimated coefficients for $\kappa_{i,R,t}$ in
the time fixed effects specifications are negative, with statistical significance displayed
in only Model 15. However, the race coefficient is still positive and significant at the
1% level, again suggesting blacks faced higher opportunity costs of schooling relative
to white students. In both tests, we note that the time fixed effects increase in magnitude by decade, and display higher levels of statistical significance through later dates.
3.6 Conclusion

This paper presents a novel data set in which values for black and white per-pupil educational expenditures were constructed to test the values generated by a dynamic, dynastic human capital model developed by Tamura, Simon, and Murphy (2016). The results of the empirical exercises suggest the model carries substantial explanatory power in terms of accuracy of the initial calibrations, and also provides substantial policy implications regarding the unequal access to education faced by black families during the Jim Crow era.

This paper makes a number of substantial contributions to the literature regarding both human capital accumulation and unequal access to education. First, by developing and presenting a novel data set in which we can account for differences between per-pupil expenditures for white and black students as well as producing estimates for the share of educational expenses allocated to white and black in conjunction with the role these metrics play in determining the relative efficiency of schooling between whites and blacks at the state level, we provide evidence of the validity of the model developed by Tamura, Simon, and Murphy (2016). These results also give measures of inequality faced by blacks relative to whites during Jim Crow.

The statistical analyses provide evidence to support the solutions to the model developed by Tamura, Simon, and Murphy (2016) in that it confirms the fit of key educational efficiency parameters calibrated in the initial theoretical framework. Our results suggest that as blacks faced unequal access to education relative to their white cohort, their costs of attendance were much higher, thereby spending less time in school than whites. As human capital is passed down inter-generationally from parents to their children, parents with low levels of schooling will likely raise children with similarly low levels of schooling as well. These results provide serious implica-
tions regarding the effects of race-based segregationist policy in the United States, as suggested by consistently lower high school graduation rates of blacks relative to whites even after the end of Jim Crow and the removal of other racially discriminatory institutionalized barriers to the equal access to public facilities (including education).

Given the nature of the inter-generational spillovers of human capital from the parents to their children, the data presented within this paper suggest that for the time sample provided, 8 decades of segregation and racial discrimination lead to black families facing substantial challenges up in the accumulation of human capital relative to whites. The results from this paper are robust to changes in the specification and transformations on the data, and all suggest a similar result; unequal access to education reduced the ability of black families to develop and pass on human capital to the next generation relative to whites, and the ramifications of Segregation era policy in the South are still experienced to this day.
Bibliography


Appendices
### Appendix A  Bank Lending and the Risk Channel of Monetary Policy Appendices

#### A.1  Data and Sources

Table 7: Data and Sources

<table>
<thead>
<tr>
<th>Variable</th>
<th>Source</th>
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</thead>
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<tr>
<td>Real GDP</td>
<td>Federal Reserve Economic Database (FRED)</td>
</tr>
<tr>
<td>Consumer Prices</td>
<td>Federal Reserve Economic Database (FRED)</td>
</tr>
<tr>
<td>Reserve Balances</td>
<td>Federal Reserve Economic Database (FRED)</td>
</tr>
<tr>
<td>10 Year Treasury Yield</td>
<td>Federal Reserve Economic Database (FRED)</td>
</tr>
<tr>
<td>Bank Lending Standards</td>
<td>Federal Reserve Economic Database (FRED)</td>
</tr>
<tr>
<td>Bank Lending Margins</td>
<td>Federal Reserve Economic Database (FRED)</td>
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<td>Shadow Federal Funds Rate</td>
<td>Jing Cynthia Wu’s Webpage</td>
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<tr>
<td>Effective Federal Funds Rate</td>
<td>Federal Reserve Economic Database (FRED)</td>
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<td>Interest on Excess Reserves</td>
<td>Federal Reserve Economic Database (FRED)</td>
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- Brazil
- Chile
- China
- Colombia
- Czech Republic
- Hungary
- India
- Mexico
- Poland
- Russia
- South Korea
- Turkey

Figure 18: Emerging Market Economy Equity Price Impulse Responses

- Brazil
- Chile
- China
- Colombia
- Czech Republic
- Hungary
- India
- Mexico
- Poland
- Russia
- South Korea
- Turkey
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Appendix C  Black and White Schooling Differentials Appendices

C.1  Data Appendix

C.1.1  Alabama

Per-pupil expenditures data for 1890, 1910, 1935, and 1950 are from Race and Schooling in the South, 1880-1950: An Economic History, and are reported in 1950 dollars. We adjust these figures for inflation to their respective years. Expenditures for 1929 and 1944 are from “The Education of Negroes in Alabama”.

C.1.2  Arkansas

Per-pupil expenditure data for 1910, 1935, and 1950 come from Race and Schooling in the South, 1880-1950: An Economic History. The available data are for 1910, 1935, and 1950, and are reported in 1950 dollars, thus we adjust these values for inflation to their respective years. We geometrically interpolate the missing data.

C.1.3  Delaware

Per-pupil expenditures for 1910, 1935, and 1950 are from Race and Schooling in the South, 1880-1950: An Economic History. The available data are for 1910, 1935, and 1950, and are reported in 1950 dollars, thus we adjust these values for inflation to their respective years.

C.1.4  Florida

Per-pupil expenditure data for 1890 and 1950 are from Race and Schooling in the South, 1880-1950: An Economic History. The 1890 value is reported in 1950
dollars, so it is adjusted for inflation. Expenditure data for 1900, 1905, 1910, 1915, 1920, 1925, 1928, 1930, 1935, 1936, 1939, and 1940 are from various releases of the *Biennial Report of the Superintendent of Public Instruction of the State of Florida*. We geometrically interpolate missing data.

### C.1.5 Georgia


### C.1.6 Kentucky

Per-pupil expenditure data for Kentucky were not available and thus this state is omitted from the analysis.

### C.1.7 Louisiana

Data for Louisiana regarding per-pupil expenditures come from “The Education of Negroes in Louisiana”. We next pull from *Race and Schooling in the South, 1880-1950: An Economic History* for the years 1890, 1910, 1935, and 1950. Data from this source are reported in 1950 dollars, and we thus adjust all of the values for inflation to their respective years. The data available for per-pupil expenditures are for 1890 through 1965 for both black and white students. Values that were not available in our sources are geometrically interpolated.
C.1.8 Maryland

Per-pupil expenditure data for the years 1890, 1910, 1935, and 1950 come from *Race and Schooling in the South, 1880-1950: An Economic History*. Data for 1929 and 1944 come from “The Education of Negroes in Louisiana”. Values missing from our sources were geometrically interpolated. These years are reported in 1950 dollars, so we adjust all values for inflation to their respective years. Data for 1920, 1925-1930, 1940, came from *The Annual Report of the State Board of Education* for Maryland for their respective years and 1944 came from “The Education of Negroes in Maryland”, published in *The Journal of Negro Education*.

C.1.9 Mississippi

Per-pupil expenditure data for the years 1890, 1910, 1935, and 1950 come from *Race and Schooling in the South, 1880-1950: An Economic History*. Data from this source are reported in 1950 dollars, and we thus adjust all of the values for inflation to their respective years. Data for 1929 come from “The Education of Negroes in Mississippi”. Missing values were geometrically interpolated.

C.1.10 North Carolina

Per-pupil expenditure data for 1890, 1910, 1935, and 1950 come from *Race and Schooling in the South, 1880-1950: An Economic History*. These data are reported in 1950 dollars and are thus adjusted for inflation. Data for 1904, 1909, 1914, 1919, and 1930 come from various reports of the superintendent of public instruction for North Carolina. Data for 1929 and 1944 are taken from “The Education of Negroes in North Carolina”, published in *The Journal of Negro Education*. Missing values were geometrically interpolated.
C.1.11 Oklahoma

Per pupil expenditure data for 1929 and 1944 come from “The Education of Negroes in Mississippi”, published in The Journal of Negro Education. Years with data that were not available between these values were geometrically interpolated.

C.1.12 South Carolina

Per-pupil expenditure data for 1910, 1935, and 1950 come from Race and Schooling in the South, 1880-1950: An Economic History. These data are reported in 1950 dollars, and are thus adjusted for inflation to their respective years. Data for 1929 and 1944 are taken from “The Education of Negroes in North Carolina”, published in The Journal of Negro Education. Values between these years that were not available in our sources were geometrically interpolated.

C.1.13 Tennessee

Per-pupil expenditure data for 1910, 1935, and 1950 come from Race and Schooling in the South, 1880-1950: An Economic History. These data are reported in 1950 dollars, and are thus adjusted for inflation to their respective years. Data for 1929 and 1944 are taken from “The Education of Negroes in Tennessee”, published in The Journal of Negro Education.

C.1.14 Texas

Per-pupil expenditure data for 1910, 1935, and 1950 come from Race and Schooling in the South, 1880-1950: An Economic History. These data are reported in 1950 dollars, therefore we adjust these values for inflation to their respective years. Class size data are not available. Missing values were geometrically interpolated.
C.1.15 Virginia

For per-pupil expenditures, data for 1890, 1910, 1935, and 1950 come from *Race and Schooling in the South, 1880-1950: An Economic History*. These values are provided in 1950 dollars, and are thus adjusted for inflation to their respective years. Data for 1941 and 1943 come from the *Annual Report of the Superintendent of Public Instruction* for their respective years. Missing values were geometrically interpolated.

C.1.16 West Virginia

Per-pupil expenditures and class size data for West Virginia were not available and thus this state is omitted from the analysis.
### Table 8: Occupations Included in Earnings Imputations

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Occupation</th>
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</thead>
<tbody>
<tr>
<td>Advertising Agents and Salesmen</td>
<td>Dressmakers and Seamstresses, Not Factory</td>
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<tr>
<td>Apprentices, Building Trades</td>
<td>Dyers</td>
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<td>Artists and Art Teachers</td>
<td>Editors and Reporters</td>
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<td>Attendants and Assistants, Library</td>
<td>Electrical Engineers</td>
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<td>Attendants, Hospital and Other Inst.</td>
<td>Electricians</td>
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<td>Attendants, Physicians And Dentists Office</td>
<td>Electrician Apprentice</td>
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<td>Bakers</td>
<td>Electrotypers and Stereotypers</td>
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<td>Barbers, Beauticians, And Manicurists</td>
<td>Engravers</td>
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<td>Blacksmiths</td>
<td>Entertainers</td>
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<td>Boarding And Lodging House Keepers</td>
<td>Express Messengers and Railway Mail Clerks</td>
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<td>Boatmen, Canalmen, And Lock Keepers</td>
<td>Farm and Home Management Advisors</td>
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<td>Boilermakers</td>
<td>Farm Foremen</td>
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<td>Brakemen, Railroad</td>
<td>Farm Laborers-Unpaid Family Workers</td>
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<td>Brickmasons, Stonemasons, and Tile Setters</td>
<td>Farm Laborers-Wage Workers</td>
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<td>Buyers and Dept. Heads, Store</td>
<td>Farm Managers</td>
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<td>Buyers and Shippers, Farm Products</td>
<td>Farmers (Owners and Tenants)</td>
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<td>Carpenters</td>
<td>Fillers/Grinders/Polishers (Metal)</td>
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<td>Cement and Concrete Finishers</td>
<td>Firemen</td>
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<td>Chairmen, Rodmen, and Axemen, Surveying</td>
<td>Fishermen</td>
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<td>Chemists</td>
<td>Foremen</td>
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<td>Civil Engineers</td>
<td>Funeral Directors and Embalmers</td>
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<td>Clergymen</td>
<td>Furnacemen, Smeltermen, and Pourers</td>
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<td>Clerical and Kindred Workers</td>
<td>Guards, Watchmen, and Doorkeepers</td>
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<td>Collectors, Bill and Account</td>
<td>Heat Treaters, Annealers, Temperers</td>
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<td>Compositors and Typesetters</td>
<td>Heaters, Metal</td>
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<tr>
<td>Conductors, Bus, Street, and Railway</td>
<td>Housekeepers (Not Private Household)</td>
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<tr>
<td>Conductors, Railroad</td>
<td>Housekeepers (Private Household)</td>
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<td>Cooks, Except Private Household</td>
<td>Hucksters and Peddlers</td>
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<td>Credit Men</td>
<td>Inspectors</td>
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<td>Decorators and Window Dressers</td>
<td>Inspectors (Public Administration)</td>
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<td>Deliverymen and Routemen</td>
<td>Inspectors, Scalers, and Graders (Log Admin)</td>
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<td>Dentists</td>
<td>Insurance Agents and Brokers</td>
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<td>Jailors and Sextons</td>
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<td>Draftsmen</td>
<td>Jewelers, Watchmakers, Goldsmiths</td>
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<td></td>
<td>Laborers</td>
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<td>Occupation</td>
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<tr>
<td>---------------------------------------------------------------------------</td>
<td>---------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Laundry and Dry Cleaning Operatives</td>
<td>Physicians and Surgeons</td>
</tr>
<tr>
<td>Laywers and Judges</td>
<td>Plasterers</td>
</tr>
<tr>
<td>Librarians</td>
<td>Plumbers and Pipe Fitters</td>
</tr>
<tr>
<td>Linemen and Servicemen, Telegraph, Telephone</td>
<td>Plumbers and Pipe Fitters (Apprentice)</td>
</tr>
<tr>
<td>Locomotive Engineers</td>
<td>Policemen and Detectives</td>
</tr>
<tr>
<td>Locomotive Firemen</td>
<td>Postmasters</td>
</tr>
<tr>
<td>Loom Fixers</td>
<td>Power Station Operatives</td>
</tr>
<tr>
<td>Laywers and Judges</td>
<td>Practical Nurses</td>
</tr>
<tr>
<td>Librarians</td>
<td>Pressmen and Plate Printers (Printing)</td>
</tr>
<tr>
<td>Lawyers and Judges</td>
<td>Private Household Workers</td>
</tr>
<tr>
<td>Laywers and Judges</td>
<td>Professional Household Workers</td>
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<tr>
<td>Librarians</td>
<td>Purchasing Agents and Buyers</td>
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<tr>
<td>Linemen and Servicemen, Telegraph, Telephone</td>
<td>Railroad Repairmen</td>
</tr>
<tr>
<td>Locomotive Engineers</td>
<td>Real Estate Agents and Brokers</td>
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<tr>
<td>Locomotive Firemen</td>
<td>Rollers and Roll Hands</td>
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<tr>
<td>Loom Fixers</td>
<td>Roofers and Slaters</td>
</tr>
<tr>
<td>Laywers and Judges</td>
<td>Sailors and Deck Hands</td>
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<tr>
<td>Librarians</td>
<td>Salesmen and Sales Clerks</td>
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<tr>
<td>Linemen and Servicemen, Telegraph, Telephone</td>
<td>Sawyers</td>
</tr>
<tr>
<td>Locomotive Engineers</td>
<td>Service Workers (not Private Household)</td>
</tr>
<tr>
<td>Locomotive Firemen</td>
<td>Sheriffs and Bailiffs</td>
</tr>
<tr>
<td>Loom Fixers</td>
<td>Shipping and Receiving Clerks</td>
</tr>
<tr>
<td>Laywers and Judges</td>
<td>Shoemakers/Repairers (Not Factory)</td>
</tr>
<tr>
<td>Librarians</td>
<td>Social Workers</td>
</tr>
<tr>
<td>Linemen and Servicemen, Telegraph, Telephone</td>
<td>Sports Officials and Instructors</td>
</tr>
<tr>
<td>Locomotive Engineers</td>
<td>Stationary Engineers</td>
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<tr>
<td>Locomotive Firemen</td>
<td>Stationary Firemen</td>
</tr>
<tr>
<td>Loom Fixers</td>
<td>Stoneographers, Typists, and Secretaries</td>
</tr>
<tr>
<td>Laywers and Judges</td>
<td>Stock and Bond Salesmen</td>
</tr>
<tr>
<td>Librarians</td>
<td>Structural Metal Workers</td>
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<tr>
<td>Linemen and Servicemen, Telegraph, Telephone</td>
<td>Professors and Instructors</td>
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<tr>
<td>Locomotive Engineers</td>
<td>Switchmen, Railroad</td>
</tr>
<tr>
<td>Locomotive Firemen</td>
<td>Tailors and Tailoresses</td>
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<td>Loom Fixers</td>
<td>Teachers</td>
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<td>Laywers and Judges</td>
<td>Teamsters</td>
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<td>Librarians</td>
<td>Telegraph Operators</td>
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<td>Linemen and Servicemen, Telegraph, Telephone</td>
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<table>
<thead>
<tr>
<th>Occupation</th>
<th>Imputed Occupation</th>
</tr>
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<tbody>
<tr>
<td>Testing Technicians</td>
<td>Waiters and Waitresses</td>
</tr>
<tr>
<td>Therapists and Healers</td>
<td>Watchmen (Crossing) and Bridge Tenders</td>
</tr>
<tr>
<td>Ticket Station, and Express Agents</td>
<td>Welders and Flame Cutters</td>
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<tr>
<td>Upholsterers</td>
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</tbody>
</table>

Table 10: Occupations Included in Earnings Imputations (Continued)
C.3 Per Pupil Expenditures

Figure 132: Alabama Log Per Pupil Expenditures (Nominal)

Figure 133: Arkansas Log Per Pupil Expenditures (Nominal)
Figure 134: Delaware Log Per Pupil Expenditures (Nominal)

Figure 135: Florida Log Per Pupil Expenditures (Nominal)
Figure 136: Georgia Log Per Pupil Expenditures (Nominal)

Figure 137: Louisiana Log Per Pupil Expenditures (Nominal)
Figure 138: Maryland Log Per Pupil Expenditures (Nominal)

Figure 139: Mississippi Log Per Pupil Expenditures (Nominal)
Figure 140: North Carolina Log Per Pupil Expenditures (Nominal)

Figure 141: South Carolina Log Per Pupil Expenditures (Nominal)
Figure 142: Tennessee Log Per Pupil Expenditures (Nominal)

Figure 143: Texas Log Per Pupil Expenditures (Nominal)
Figure 144: Virginia Log Per Pupil Expenditures (Nominal)
C.4 Earnings Data

Figure 145: Alabama Log Earnings (Nominal)

Figure 146: Arkansas Log Earnings (Nominal)
Figure 147: Delaware Log Earnings (Nominal)

Figure 148: Florida Log Earnings (Nominal)
Figure 149: Georgia Log Earnings (Nominal)

Figure 150: Louisiana Log Earnings (Nominal)
Figure 151: Maryland Log Earnings (Nominal)

Figure 152: Mississippi Log Earnings (Nominal)
Figure 153: North Carolina Log Earnings (Nominal)

Figure 154: South Carolina Log Earnings (Nominal)
Figure 155: Tennessee Log Earnings (Nominal)

Figure 156: Texas Log Earnings (Nominal)
Figure 157: Virginia Log Earnings (Nominal)
C.5 $\kappa_{i,R,t} \tau_{i,R,t}$ Model and Data Comparisons

Figure 158: Alabama Log Kappa Tau

![Alabama Log Kappa Tau Graph]

Figure 159: Arkansas Log Kappa Tau

![Arkansas Log Kappa Tau Graph]
Figure 160: Delaware Log Kappa Tau

Figure 161: Florida Log Kappa Tau
Figure 162: Georgia Log Kappa Tau

Figure 163: Louisiana Log Kappa Tau

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Figure 164: Maryland Log Kappa Tau

Figure 165: Mississippi Log Kappa Tau
Figure 166: North Carolina Log Kappa Tau

![Graph showing North Carolina Log Kappa Tau over time with different data and model representations.]

Figure 167: South Carolina Log Kappa Tau

![Graph showing South Carolina Log Kappa Tau over time with different data and model representations.]
Figure 168: Tennessee Log Kappa Tau

![Tennessee Log Kappa Tau](image1)

Figure 169: Texas Log Kappa Tau

![Texas Log Kappa Tau](image2)
Figure 170: Virginia Log Kappa Tau

![Graph showing the trend of Virginia Log Kappa Tau over years from 1880 to 1960. The graph includes lines for different models and data sets, indicating changes and trends over time.]
C.6 $\kappa_{i,R,t}$ Model and Data Comparisons

Figure 171: Alabama Log Kappa

Figure 172: Arkansas Log Kappa
Figure 173: Delaware Log Kappa

Figure 174: Florida Log Kappa
Figure 175: Georgia Log Kappa

![Georgia Log Kappa Graph]

Figure 176: Louisiana Log Kappa

![Louisiana Log Kappa Graph]
Figure 177: Maryland Log Kappa

![Maryland Log Kappa Graph]

Figure 178: Mississippi Log Kappa

![Mississippi Log Kappa Graph]
Figure 179: North Carolina Log Kappa

Figure 180: South Carolina Log Kappa
Figure 181: Tennessee Log Kappa

Figure 182: Texas Log Kappa
Figure 183: Virginia Log Kappa

![Graph showing the trend of Virginia Log Kappa over the years from 1880 to 1960.](image-url)