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UNIVERSITY OF CALIFORNIA, SAN DIEGO

**Essays on Macroeconomics**

A dissertation submitted in partial satisfaction of the  
requirements for the degree  
Doctor of Philosophy

in

Economics

by

Erin L. Wolcott

Committee in charge:

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2017

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The dissertation of Erin L. Wolcott is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

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Chair

University of California, San Diego

2017

DEDICATION

To my mother, Constance E. Wolcott

## EPIGRAPH

*Macroeconomics. "Macro" comes from the greek word μέγαλι, which means large,  
and "economics" comes from the greek word εχονομία, which means  
to manage one's resources.*

—Papou

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ABSTRACT OF THE DISSERTATION

**Essays on Macroeconomics**

by

Erin L. Wolcott

Doctor of Philosophy in Economics

University of California, San Diego, 2017

Professor Valerie Ramey, Chair

This dissertation studies three policy-oriented macroeconomic questions. The first chapter examines whether traditional monetary policy in the U.S. becomes less effective when foreign governments accumulate large amounts of Treasury debt. I estimate a macro-finance model and find foreign official purchases have shifted the entire yield curve down. This suggests the increasing presence of international factors in U.S. financial markets influences the Federal Reserve's interest rate policy. The second chapter asks why low-skilled men are less likely to be employed relative to high-skilled men and why this differential has increased since the 1970s. I build and calibrate a labor-search model and find a demand shift and job separations are the main drivers of employment

inequality, while a supply shift had no robust effects, and search frictions actually reduced employment inequality since the 1970s. The third and final chapter studies why wages of newly hired workers are more pro-cyclical than wages of workers who do not switch jobs. We construct a novel measure of occupational mismatch by comparing a newly hired worker's current skill profile to his previous skill profile. Including our measure of occupational mismatch in standard wage regressions can account for half of the new hire wage cyclicity previously documented in the literature.

# Chapter 1

## Impact of Foreign Official Purchases of U.S. Treasuries on the Yield Curve

### 1.1 Abstract

Foreign governments went from owning 10% of publicly held U.S. Treasury debt in 1985 to over 50% in 2008. Recently, foreign governments have reduced their Treasury positions. This paper employs a Gaussian affine term structure model, augmented with macro variables, to test whether purchases of Treasuries by foreign governments have effected U.S. interest rates. The advantage of using a term structure model is it allows us to examine the impact of shocks over the entire yield curve, as opposed to a single maturity. To identify shocks to foreign official purchases of Treasuries, I embed a structural vector autoregression of macroeconomic variables in the model. I find foreign official purchases have shifted the entire yield curve down with the largest impacts on the 2-year Treasury yield.

## 1.2 Introduction

In 2005, Ben S. Bernanke, Chairman of the Federal Reserve, coined the term “global saving glut” in a speech highlighting the abundance of global savings financing the acquisition of foreign claims rather than domestic investment. Much of this global saving glut has its origins in the 1997 Asian financial crisis, where Asian emerging market economies suffered a loss of lender confidence and subsequently an outflow of capital. Since then, several countries in Asia that were previously net borrowers morphed into net lenders, building up their foreign reserves to use as a buffer against capital outflows in the wake of another crisis.

Figure 1.1 plots the rate of foreign reserve accumulation of all countries starting in 1995. The series displays a steeper slope in the early 2000s, suggesting the rate at which governments acquired foreign exchange reserves increased after the Asian financial crisis. More recently the rate of accumulation has tapered, yet the total change over the last two decades is still over 1000%. In 1995 reserves totaled about \$1 trillion, today they are over \$10 trillion.

Although the composition of foreign exchange reserves is often not publicly available, it is believed the majority of Asia’s international reserves are held in U.S. dollar assets. U.S. securities are particularly attractive to foreign governments because they are safe, liquid products denominated in the currency many emerging market economies use as a reference point on the foreign exchange market. Figure 1.2 plots the percent of publicly held Treasury securities owned by foreigners. In 1985, foreigners owned 15 percent or \$100 billion of U.S. publicly held Treasury debt, while in 2014 they owned over 60 percent or \$5 trillion. The growth in foreign holdings since the 1990s is remarkable and China and Japan’s acquisitions (blue and red regions), following the Asian financial crisis, account for a significant fraction of that growth.



To gauge how much of these foreign inflows are held by foreign governmental entities, Figure 1.3 plots the percent of publicly held Treasuries outstanding owned by foreign official agencies. Note, I will refer to flows into Treasuries by foreign governments as foreign official purchases. After the Asian financial crisis, the percent of Treasuries held by foreign official agencies immediately increased. In 2011, over 50 percent of U.S. publicly held federal debt was owned by foreign governments. More recently, foreign governments have reduced their positions of U.S. Treasuries. After comparing Figures 1.2 and 1.3, we see that the majority of foreign-held Treasury securities are in the possession of governments.

The massive increase of foreign official flows into U.S. securities begs the question of whether these purchases have depressed interest rates and altered the yield curve. This question has several important policy implications. The first regards monetary policy. If U.S. interest rates are increasingly determined by international financial markets, then it may be more difficult for the Federal Reserve to implement its interest rate policy. For instance, the Fed may find it desirable to use unconventional monetary policies to offset the effects of foreign official purchases, particularly, if these effects are concentrated at the long-end of the yield curve. Additionally, if foreign governments decide to sell off their sizable Treasury positions—as they appear to be doing since 2008—and the Fed is not prepared to implement counteractive measures, U.S. interest rates may increase and have a contractionary effect on the economy.

The second policy implication regards global financial stability. It is widely believed the recent financial crisis, at least in part, was caused by persistently low interest rates in the early 2000s, of which some economists attribute to stimulative monetary policy (see Taylor (2009); Gambacorta (2009); Maddaloni and Peydró (2011)). However, if foreign official purchases of Treasuries are part of the story for why interest rates were so low, then they too may have contributed to the financial crisis.

Previous work has asked whether the influx of foreign investment into U.S. securities has pushed down long-term interest rates in the U.S. This paper goes beyond that and asks how foreign official investment has affected the entire yield curve. I do this by estimating a Gaussian affine term structure model (ATSM), augmented with macro variables. ATSMs exploit no arbitrage in financial markets to identify factors explaining the yield curve. By embedding a structural vector autoregression (SVAR) of macro variables—one of which is foreign official purchases of Treasuries—in the model, I uncover how macro variables, in addition to three latent factors, explain the dynamics of the U.S. yield curve.

Section 1.3 reviews some key works in the foreign official positions literature and ATSM literature; Section 2.4 outlines the basic framework of ATSMs and their application to the question at hand; Section 1.5 describes the data; Section 1.6 explains the estimation strategy; Section 2.6 presents and discusses the results; and Section 2.7 concludes.

## **1.3 Related Literature**

### **1.3.1 Foreign Official Purchases**

One of the most widely cited works investigating the impact of foreign official purchases on U.S. Treasury securities is Warnock and Warnock (2009). They regress the 10-year Treasury rate on foreign official purchases for the period January 1984 to May 2005, including a number of control variables, such as short-term interest rates, inflation expectations, growth expectations, the federal deficit, and a variable capturing the interest rate risk premium. They conclude each \$100 billion Treasury purchase reduced the 10-year yield by 68 basis points. From specifications with alternative dependent variables, they also conclude foreign inflows have depressed U.S. corporate bond rates and mortgage

rates, potentially fueling the financial and housing bubbles. Their identification strategy, however, relies on assuming foreign official purchases are exogenous. Although foreign officials may not maximize returns the way private investors do, their actions are likely systematic and respond to economic circumstances.

Bernanke, Reinhart, and Sack (2004) use an event study approach to circumvent this exogeneity assumption and find a similar impact of foreign inflows on U.S. yields. Using Japanese announced foreign exchange interventions between 2000 and 2004, they find each \$100 billion intervention in the Treasury market reduced the 10-year yield by 66 basis points. Martin (2014) also uses high frequency data, but finds larger effects. Using a new measure of surprise Chinese official Treasury purchases, Martin (2014) finds the 10-year yield fell by over 100 basis points in response to a \$100 billion intervention.

Lastly, Beltran et al. (2013) use instrumental variables to relax the assumption that foreign official purchases are exogenous. They estimate the short-run impacts of foreign official purchases on the 5-year term premium with two-stage-least-squares, where instruments include an oil-specific supply shock variable, Japanese foreign exchange interventions, and the Chinese trade balance. Using data from January 1994 to June 2007, they find a smaller impact of foreign official purchases on yields. In particular, if foreign official purchases were to decrease by \$100 billion, the 5-year Treasury rate would immediately rise by 40-60 basis points. To estimate the long-term impact of foreign official purchases, after private investors react to the yield change, they employ a co-integrated VAR and find the effect is about a 20 basis point rise in yields.

This paper contributes to the foreign official purchases literature by accounting for the possibility that foreign official purchases are not exogenous and systematically examining how the entire yield curve responds instead of a particular maturity, such as the 5- or 10-year rate.

### 1.3.2 ATSM Literature

By incorporating an ATSM, this paper is the first to document the response of the entire yield curve to foreign official purchase shocks. ATSMs exploit the convenient property of bonds that different maturities of the same asset are traded at the same time. This allows the researcher to compare bond prices of varying maturities and infer something about investors' risk preferences. Specifically, ATSMs assume any gap between long-term yields and the expected value of future short-term yields is the price of risk and not an arbitrage opportunity. ATSMs essentially assume no arbitrage; and in deep markets, like the U.S. Treasury market, it is likely all arbitrage opportunities are instantaneously traded away. By imposing restrictions across maturities so long rates equal risk-adjusted future short rates, the researcher attains a parsimonious model of the entire yield curve based on only a few parameters.<sup>1</sup>

Originally, ATSMs were used to uncover latent factors explaining the yield curve. The norm was to include three latent factors and interpret them as "level," "slope," and "curvature" (see Dai and Singleton (2000), (2002); Duffee (2002); Kim and Orphanides (2005); Kim and Wright (2005)). However, Ang and Piazzesi (2003) popularized the inclusion of both observable and unobservable factors in ATSMs. Specifically, they include observed inflation and economic growth factors, along with three latent factors, to investigate how macro variables contribute to bond prices and the yield curve. They find that macro factors explain a significant portion of movements in the yield curve (up to 85%), particularly for short- and middle-length maturities.

Pericoli and Taboga (2008) similarly study ATSMs including observed macro variables. They suggest a less restrictive set of identifying restrictions than Ang and Piazzesi (2003), namely, macro variables need not be orthogonal to latent factors. Nevertheless, they also conclude shocks to output and inflation explain a significant portion of

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<sup>1</sup>See Piazzesi (2010) for a thorough survey of the literature.

yield-curve dynamics.

Hamilton and Wu (2012) show both Ang and Piazzesi (2003) and Pericoli and Taboga's (2008) canonical representations are not identified. Hamilton and Wu suggest additional restrictions and an alternative method for uncovering structural parameters from reduced-form estimates. Their minimum-chi-square approach is asymptotically equivalent to the commonly used maximum likelihood, but advantageously allows the researcher to know if estimates are at a global or only local optimum.

In what follows, I estimate an ATSM using four observed macro variables—one of which is foreign official purchases—and three unobserved latent factors. I use Hamilton and Wu's suggested identification restrictions along with their minimum-chi-square estimation.

## 1.4 Gaussian Affine Term Structure Model

### 1.4.1 The General Case

In typical macro models where a representative agent maximizes expected utility and smooths consumption using one-period bonds, the following consumption Euler equation holds:

$$P_{1,t} = \beta E_t \frac{U'(C_{t+1})}{U'(C_t)} \Pi_{t+1}^{-1}, \quad (1.1)$$

where  $P_{1,t}$  is the price of a one-period bond at time  $t$ ;  $\beta$  is the discount rate;  $U'(C_t)$  is the marginal utility of consumption; and  $\Pi_t$  is the inflation rate. The right-hand side of the equation is the expected discounted value of one dollar delivered at  $t + 1$ . Let us define the pricing kernel  $M_{t+1}$  to be the stochastic discount factor in equation (1.1), i.e.

$$M_{t+1} \equiv \beta \frac{U'(C_{t+1})}{U'(C_t)} \Pi_{t+1}^{-1}. \quad (1.2)$$

Using this pricing kernel, we can price the return of bonds. Specifically, an  $n$ -period bond is the expected discounted value of an  $n - 1$  period bond,

$$P_{n,t} = E_t M_{t+1} P_{n-1,t+1}. \quad (1.3)$$

Equation (1.3) provides a recursive condition linking bond prices across maturities.

Now let us rewrite the price of an  $n$ -period bond  $P_{n,t}$  paying one dollar at time  $t + 1$  in terms of the risk-free, one-period interest rate  $r_t$ . For a continuously compounded  $1, 2, \dots, n$ -period bond at time  $t$ , we can compute prices as follows:

$$\begin{aligned} P_{1,t} &= E_t M_{t+1} = e^{-r_t} \\ P_{2,t} &= E_t M_{t+1} P_{1,t+1} = \underbrace{E_t M_{t+1} E_t P_{1,t+1}}_{e^{-r_t} E_t e^{-r_{t+1}}} + \underbrace{Cov(M_{1+t}, P_{1,t+1})}_{\text{risk-adjustment}} \\ &\vdots \\ P_{n,t} &= E_t M_{t+1} P_{n-1,t+1}. \end{aligned} \quad (1.4)$$

The equations in (1.4) illustrate the price of a long-term bond is equal to the price a risk-neutral investor would pay plus a risk-adjustment term. In the absence of the risk-adjustment term these equations can be interpreted as no-arbitrage conditions for a risk-neutral investor. ATSMs impose this no-arbitrage condition while accounting for the risk component of bond prices.

In order to bring this structure to data, we assume a particular functional form for the pricing kernel. Affine term structure models assume the following:

$$M_{t+1} = \exp\left[-r_t - \frac{1}{2} \lambda_t' \lambda_t - \lambda_t' u_{t+1}\right], \quad (1.5)$$

where  $\lambda_t$  characterizes investor attitude toward risk. Note that  $\lambda_t = 0$  corresponds to risk

neutrality and the strong form of the expectations hypothesis.<sup>2</sup>

Gaussian affine term structure models make four additional assumptions. First, factors underlying interest rates, denoted  $F_t$ , are assumed to be an affine function of their lags,

$$F_t = c + \rho F_{t-1} + \Sigma u_t. \quad (1.6)$$

Next, the residuals of equation (1.6) are assumed to be Gaussian,

$$u_t \sim \text{i.i.d.} N(0, I), \quad (1.7)$$

which implies that  $F_{t+1} | F_t, F_{t-1}, \dots, F_1 \sim N(\mu_t, \Sigma \Sigma')$  for  $\mu_t = c + \rho F_t$ . ATSMs further assume the market price of risk is itself an affine function of  $F_t$ ,

$$\lambda_t = \lambda_0 + \lambda_1 F_t. \quad (1.8)$$

Lastly, ATSMs assume the short rate  $r_t$  is an affine function of the factors,

$$r_t = \delta_0 + \delta_1' F_t. \quad (1.9)$$

Given assumptions (1.5)-(1.9), it can be shown an  $n$ -period bond yield (defined as  $y_{n,t} \equiv -\frac{1}{n} \ln P_{n,t}$ ) can be written as an affine function of the factors,<sup>3</sup>

$$y_{n,t} = \alpha_n + \beta_n' F_t, \quad (1.10)$$

---

<sup>2</sup>The strong form of the expectations hypothesis is in contrast to what Gürkaynak and Wright (2012) refer to as the weak form, which allows for maturity-specific term premia to be constant over time.

<sup>3</sup>See Ang and Piazzesi's (2003) Appendix 1.9 for a derivation.

where the constant and slope coefficients take the following recursive formulations:

$$\alpha_n = -\frac{1}{n}(-\delta_0 + \alpha_{n-1} + \beta'_{n-1}c - \beta'_{n-1}\Sigma\lambda_0 + \frac{1}{2}\beta'_{n-1}\Sigma\Sigma'\beta_{n-1}) \quad (1.11)$$

$$\beta_n = -\frac{1}{n}(-\delta_1 + \beta'_{n-1}\rho - \beta'_{n-1}\Sigma\lambda_1). \quad (1.12)$$

Equations (1.10)-(12) reveal that given  $\{c, \rho, \lambda_0, \lambda_1, \delta_0, \delta_1, \Sigma\}$  and  $F_t$ , we can calculate the yield of any bond.

## 1.4.2 The Foreign Official Purchase Application

Following Ang and Piazzesi (2003) and Hamilton and Wu (2012), I estimate a macro finance model. My model differs from the literature by letting  $N_m = 4$  observed macro factors explain yields, namely, output growth, inflation, exchange rate movements, and net foreign official purchases of U.S. Treasuries.<sup>4</sup> I stack these variables in a  $(N_m \times 1)$  vector  $f_t^m$ . In addition, I use  $N_\ell = 3$  latent factors stacked in the  $(N_\ell, \times 1)$  vector  $f_t^\ell$ .

$$F_t = \begin{bmatrix} f_t^m \\ f_t^\ell \end{bmatrix}, \quad (1.13)$$

where  $F_t$  is a vector containing  $N_m + N_\ell$  elements. The factor dynamics in (1.6) and risk-free yield equation in (1.9) can be partitioned as follows:

$$f_t^m = c_m + \rho_{mm}f_{t-1}^m + \rho_{m\ell}f_{t-1}^\ell + \Sigma_{mm}u_t^m \quad (1.14a)$$

$$f_t^\ell = c_\ell + \rho_{\ell m}f_{t-1}^m + \rho_{\ell\ell}f_{t-1}^\ell + \Sigma_{\ell m}u_t^m + \Sigma_{\ell\ell}u_t^\ell \quad (1.14b)$$

$$r_t = \delta_0 + \delta'_{1m}f_t^m + \delta'_{1\ell}f_t^\ell. \quad (1.14c)$$

---

<sup>4</sup>Ang and Piazzesi (2003), Pericoli and Taboga (2008), and Smith and Taylor (2009) use  $N_m = 2$  observed macro factors, namely, inflation and a measure of output.



Since data is monthly, (1.14a) is better suited as a VAR(12) in macro variables, rather than a VAR(1), so I impose this assumption. I also follow the literature and impose three types of identifying restrictions to equations (1.14a-c).

First, I assume macro dynamics are independent of the unobserved latent factors (i.e.  $\rho_{m\ell}, \rho_{\ell m} = 0$ ). Then, I assume a Cholesky identification scheme for the macro variables (i.e.  $\Sigma_{mm}$  is lower triangular). This implies that variables ordered last in vector  $f_t^m$  do not contemporaneously impact the other macro variables. The goal of this paper is to identify shocks of foreign official purchases, so I order this variable last to allow foreign officials to react to contemporaneous growth, inflation, and volatility, but not vice versa. Together these first two assumptions allow me to estimate a SVAR in the macro variables, which is independent from the latent variables, to identify how innovations in foreign official purchases impact macro outcomes. I then feed these predictions into the ATSM model—since equations (1.10)-(12) give closed-form solutions for how macro factors influence yields—to trace out the implied path of yields.

The next set of identifying assumptions are normalizations. I assume  $\rho_{\ell\ell}$  is lower triangular with diagonal elements ordered as follows  $\rho_{\ell\ell(1,1)} \geq \rho_{\ell\ell(2,2)} \geq \rho_{\ell\ell(3,3)}$ . As discussed in Hamilton and Wu (2012), without restrictions on  $\rho_{\ell\ell}$ , there are multiple parameter configurations of the latent variables leading to observationally equivalent yields. I choose one set of restrictions so the model is identified, but this is without economic content since other choices would result in the same implied path for yields. Additionally, I assume  $\Sigma_{\ell\ell} = I_{N_\ell}$ , meaning the 3 latent factors are orthogonal to each other. Last, I assume  $c_\ell, c_m = 0$ , which is inconsequential since it normalizes the latent factors and, as stated in the next section, I demean the macro variables.

The final set of restrictions ensures there is not an overabundance of structural parameters to recover from the reduced form in Section 1.6. Ang and Piazzesi (2003) attempt to improve the efficiency of their model by fixing parameters with large standard

errors in the first stage to zero, but Hamilton and Wu (2012) show at least one of these restrictions is in fact needed for their model to be identified. Therefore, I impose one of Ang and Piazzesi's ad-hoc zero restrictions for identification purposes. In particular, I set the last element of  $\lambda_0$  to zero.<sup>5</sup> This means the time-varying risk associated with the third latent factor, which is the (1,7) element of  $\lambda_t$ , is not an affine function of the factors (i.e.  $\lambda_{t(1,7)} = \lambda_{0(1,7)} + \lambda_{1(1,7)}F_t$ ), but rather a linear combination of the factors (i.e.  $\lambda_{t(1,7)} = \lambda_{1(1,7)}F_t$ ).<sup>6</sup>

By altering the lag structure and including the above identifying restrictions, (1.14a-c) becomes:

$$f_t^m = \rho_1 f_{t-1}^m + \rho_2 f_{t-2}^m + \dots + \rho_{12} f_{t-12}^m + \Sigma_{mm} u_t^m \quad (1.15a)$$

$$f_t^\ell = \rho_{\ell\ell} f_{t-1}^\ell + u_t^\ell \quad (1.15b)$$

$$r_t = \delta_0 + \delta'_{1m} f_t^m + v_t. \quad (1.15c)$$

Since I assume the latent factors  $f_t^\ell$  are orthogonal to the macro factors  $f_t^m$ , the short rate  $r_t$  in equation (15c) can be interpreted as arising from a version of the Taylor rule, where the error  $v_t = \delta'_{1\ell} f_t^\ell$  is the unpredictable component of monetary policy. The policy rule recommended by Taylor (1993) specifies how the central bank should react to changes in output and inflation when setting the short rate. Here, I allow the central bank to react to all macro variables in  $f_t^m$ , namely, output growth, inflation, exchange rates, and foreign demand for Treasuries. The Federal Reserve considers hundreds of variables when conducting monetary policy. This approach is simply a more general treatment of the monetary policy rule assumed by Ang and Piazzesi (2003).<sup>7</sup> I directly

<sup>5</sup>Following Ang and Piazzesi (2003) I assume parameters in  $\lambda_0$  and  $\lambda_1$  correspond to only current macro and latent variables, not lagged macro variables, so that  $\lambda_0$  contains  $N_m + N_\ell = 7$  parameters.

<sup>6</sup>Ang and Piazzesi (2003) assume that the risk associated with all the macro factors and all but the first latent factor is a linear combination of the factors rather than an affine function. They also impose additional ad-hoc zero restrictions on the slope parameters of latent factor risk  $\lambda_{1\ell\ell}$ .

<sup>7</sup>Ang and Piazzesi perform specification tests for including lags of inflation and real activity in their

obtain values of  $\delta_0$  and  $\delta_{1m}$  from OLS estimation of equation (15c). Recovering the remaining parameters is more involved and Section 1.6 describes the process.

## 1.5 Data

Time series data for net foreign official purchases of U.S. Treasury securities is from Bertaut and Tryon (2007) and Bertaut and Judson (2014).<sup>8</sup> Treasury International Capital (TIC) system reports foreign and foreign official net purchases, but as acknowledged by Warnock and Warnock (2009) and others, there are major issues with the data. For example, the system cannot differentiate between foreign official investors and private investors when the transaction goes through a third-country intermediary. This is potentially a very confounding feature because governments of oil-exporting countries are thought to accumulate large amounts of Treasuries through intermediary countries. Bertaut and Tryon (2007) and Bertaut and Judson (2014) work with other sets of cross-boarder securities data to correct these issues and publish an adjusted series of monthly purchases. The exact variable I use in this analysis is net foreign official purchases, scaled by the value of Treasuries outstanding held by the public. Data for total Treasury securities outstanding minus the amount held in U.S. government accounts and Federal Reserve Banks is from the Center for Research in Security Prices (CRSP) and is the historical 12-month moving average to eliminate seasonality. Appendix 1.9 shows why scaling net foreign official purchases by Treasuries outstanding is necessary to obtain a stationary series.

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Taylor rule estimation. They find mixed results and thus estimate two ATSMs, one including a Taylor rule based on only contemporaneous variables, which they refer to as the "Macro Model" and another including a Taylor rule that incorporates lags, which they refer to as the "Macro Lag Model." I estimate an ATSM with a monetary policy rule that only depends on contemporaneous variables, but includes four rather than two macro variables.

<sup>8</sup>Data is available for download at <http://www.federalreserve.gov/pubs/ifdp/2007/910/ticdata.zip> and [http://www.federalreserve.gov/pubs/ifdp/2014/1113/ifdp1113\\_data.zip](http://www.federalreserve.gov/pubs/ifdp/2014/1113/ifdp1113_data.zip).

Data for the remaining baseline macro factors is from the FRED database of the Federal Reserve Bank of St. Louis. This includes U.S. output growth and inflation, which are the 12-month percentage change in industrial production and CPI. Since the Japan hold a large share of U.S. Treasuries, the baseline exchange rate factor is the Yen/USD rate. I check robustness to a broad measure of U.S. exchange rates in Appendix 1.12.

The  $N_\ell = 3$  latent factors are estimated using monthly data on  $N = 6$  bond yields. In order to explain 3 latent factors using 6 yields, I follow the literature and assume 3 yields contain measurement error. Specifically, I assume the 1-, 3-, 6-year bond yields are priced *without* error,  $Y_t^1 = (y_t^{12}, y_t^{36}, y_t^{72})'$  and the 2-, 4-, 5-year bond yields are priced *with* error,  $Y_t^2 = (y_t^{24}, y_t^{48}, y_t^{60})'$ . I use the 1-year yield  $y_t^{12}$  as a proxy for the observed short rate  $r_t$ .<sup>9</sup> Yields are constructed using zero-coupon yields from Gürkaynak, Sack, and Wright (2007) and are divided by 1200 in order to convert to monthly fractional rates. The sample period runs from January 1985 through August 2014.<sup>10</sup>

## 1.6 Estimation

Hamilton and Wu (2012) show Gaussian affine term structure models, where exactly  $N_\ell$  linear combinations of yields are assumed to be priced without error, can be written as a restricted vector autoregression. Imposing the assumptions outlined in Section 1.4.2, which allow for one lag of the  $N_\ell$  latent factors and 12 lags of the  $N_m$

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<sup>9</sup>Term structure models often use the 3-month yield to proxy for the observed short rate; however, the 3-month and 1-year are highly correlated with a correlation coefficient of 0.994 over 1985-2014.

<sup>10</sup>The sample period ends in August 2014 to exclude the spike in publicly held Treasuries outstanding, starting in September 2014.

macro variables, results in the following reduced form:

$$f_t^m = \Phi_{mm}^* F_{t-1}^m + u_{mt}^* \quad (1.16a)$$

$$Y_t^1 = A_1^* + \Phi_{1m}^* F_{t-1}^m + \Phi_{11}^* Y_{t-1}^1 + \Psi_{1m}^* f_t^m + u_{1t}^* \quad (1.16b)$$

$$Y_t^2 = A_2^* + \Phi_{2m}^* F_t^m + \Phi_{21}^* Y_t^1 + u_{2t}^*, \quad (1.16c)$$

where  $F_t^m$  is a  $12 \times N_m$  element vector of contemporaneous and lagged macro variables;  $F_{t-1}^m$  is a  $12 \times N_m$  element vector of lagged macro variables;  $Y_{t-1}^1$  is an  $N_\ell$  element vector of the one-month lags of exactly priced yields; and  $Y_{t-1}^2$  is an  $N - N_\ell$  element vector of the one-month lags of yields priced with error.

The mapping between the structural and reduced-form parameters for the  $N_m = 4$ ,  $N_\ell = 3$ , and  $N = 6$  case can be found in Appendix 1.10. The system in Appendix 1.10 satisfies the necessary conditions for identification. In fact, the system is over-identified; it contains more estimated reduced-form parameters (535) than unknown structural parameters (516). I obtain the reduced-form coefficients from estimating equations (1.16a-c) via OLS. I then use Hamilton and Wu's minimum-chi-square estimation strategy to recover the structural parameters. The system converges and is robust to many initializations.

## 1.7 Results

The impact of each factor on an  $n$ -length bond is determined by the weights in  $\beta_n$ . The first four rows of  $\beta_n$  are the initial response of yields to shocks in the four factors (recall equation (1.10)). Figure 1.4 plots these factor loadings as a function of yield maturity. Responses have been scaled to correspond to movements of a one standard deviation of the factors. Note that  $\beta_n$  is first multiplied by 1200 to annualize and then

multiplied by 100 to convert to basis points.

Figure 1.4 reveals the macro factors, relative to the latent factors, can explain a significant portion of movements in the yield curve. Shocks to inflation shift the entire yield curve up, with the largest impacts at the short end of the curve. Shocks to output growth also shift the yield curve up, but effects are more uniform across maturities. In contrast, shocks to the Yen/USD exchange rate and to foreign official purchases shift the yield curve down. The negative contribution of foreign official purchases aligns with our hypothesis that an increase in demand for Treasuries by foreign governments depresses yields. Moreover, the effect is non-linear in maturity length: the 2-year rate fell more than any other maturity, in response to a foreign official purchase shock.

Figure 1.5, displays impulse response functions of yields to a one standard deviation shock in the macro variables.<sup>11</sup> Responses of six maturities are plotted. Starting with the upper left corner, we see output growth is associated with a rise in yields. As the U.S. economy grows, investors pull out of safe assets, such as Treasury securities, resulting in elevated yields.

Moving to the upper right plot, we see inflation is associated with a rise in nominal rates with the largest increases at the short end for the curve. The correlation of yields with inflation is less persistent than that with output growth; within 16 months it subsides to zero. Since nominal rates are the sum of real rates and inflation, it is not surprising there is a positive short-term relationship between the two variables.

The lower left plot shows dollar appreciation against the Yen is associated with a decline of U.S. yields on impact. After controlling for U.S. output and inflation a shock to the Yen/USD exchange rate puts downward pressure on Treasury yields. Japanese policy makers likely respond to a shock of this type by buying U.S. Treasuries with the goal of devaluing the Yen and keeping Japanese exports competitive. In turn, these

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<sup>11</sup>See Appendix 1.11 for impulse response functions of the macro variables in response to macro shocks, before the implied effects are traced out for yields.

purchased depress U.S. yields. Two years after dollar appreciation, U.S. yields increase. At this point, the effect of private investors dumping U.S. assets because of the elevated exchange rate, likely dominates.

Lastly, we turn to the lower right plot, the plot of interest. A one standard deviation shock to foreign official purchases, after controlling for U.S. growth, inflation, and exchange rate movements, initially reduces the 2-year rate the most by 4.4 basis points, followed by 3-year rate by 4.2 basis points. The 1-year yield initially falls 3.0 basis points, increasing in the subsequent months only to return to negative territory within the year. The longest maturity plotted, the 6-year yield, initially falls by 2.5 basis points in response to a foreign official purchase shock, and like the other longer term rates, gradually returns to zero within 4 years. Since the standard deviation of foreign official purchases is 0.31 of a percentage point, this means an inflow equal to one percent of the amount of publicly held Treasuries outstanding initially lowers the 2-year yield by 14 basis points and the 6-year yield by about 8 basis points.

Figure 1.6 zooms in on the southeast panel of Figure 1.5 and plots confidence bands on each maturity's response to a foreign official purchase shocks. Confidence bands are bootstrapped at the 90 percent level and reveal yields of all maturities likely fell and remained depressed for up to 5 years after the shock. Moreover, results are robust to specifications that include alternative sets of macro factors. Appendix 1.12 redefines a foreign official purchase shock by replacing the Yen/USD exchange rate in the SVAR with a broad index of the U.S. exchange rate.

Differences in the points estimates between 1-year, 2-year, 3-year, etc. are not statistically significant. Nevertheless, these differences make economic sense. According to TIC, since the early 2000s a large share of foreign-held Treasuries were to mature in one to two years.<sup>12</sup> For example, in 2014, 21% of Treasuries held by foreign governments

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<sup>12</sup>TIC began publishing a chart of the maturity structure of foreign official holdings in 2004

were to mature in one to two years, while 17% were to mature in less than a year, and 19% were to mature in two to three years. Shares of foreign government Treasuries maturing after three years monotonically decline.<sup>13</sup> In other words, the type of securities foreign governments own the most of are the type of securities whose prices have been most affected by their purchases.

These results are on par with previous work. Recall that Beltran et al. (2013) examine the impact of foreign official purchase shocks on only the 5-year yield. They find that an inflow equal to one percent of the amount of Treasuries outstanding lowers the 5-year yield by 13.5 basis points when using their two-stage-least-squares approach, and 5-6 basis points when using their VAR approach. I find a consistent impact for the 5-year yield of about 10 basis points.

Unlike the aforementioned paper, however, I examine how foreign official purchases influence the dynamics of the entire yield curve. I find the impact of foreign official purchases is statistically significant and depresses rates of all maturities with effects lingering for up to 5 years. Because foreigners buy a large share of 2-year Treasuries, I find the 2-year yield is most affected by foreign official purchases. Foreign governments have accumulated over 40 additional percentage points of publicly held Treasuries outstanding from 1985 to 2008 (as illustrated in Figure 1.3). The above findings suggest interest rates, especially the 2-year, would have been considerably higher in the absence of foreign official purchases. Moreover, since 2008 foreign governments have offloaded 10 percentage points of publicly held Treasuries. If this trend continues, it may put upward pressure on U.S. interest rates.

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<sup>13</sup><http://ticdata.treasury.gov/Publish/shl2014r.pdf>

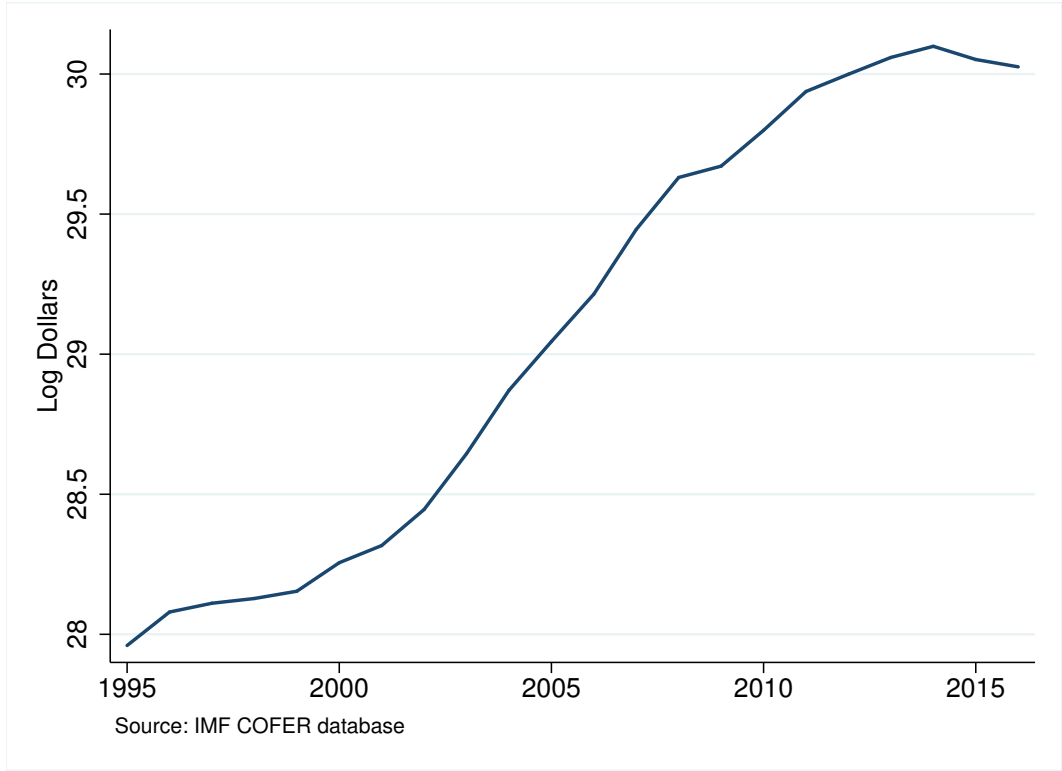


## 1.8 Conclusion

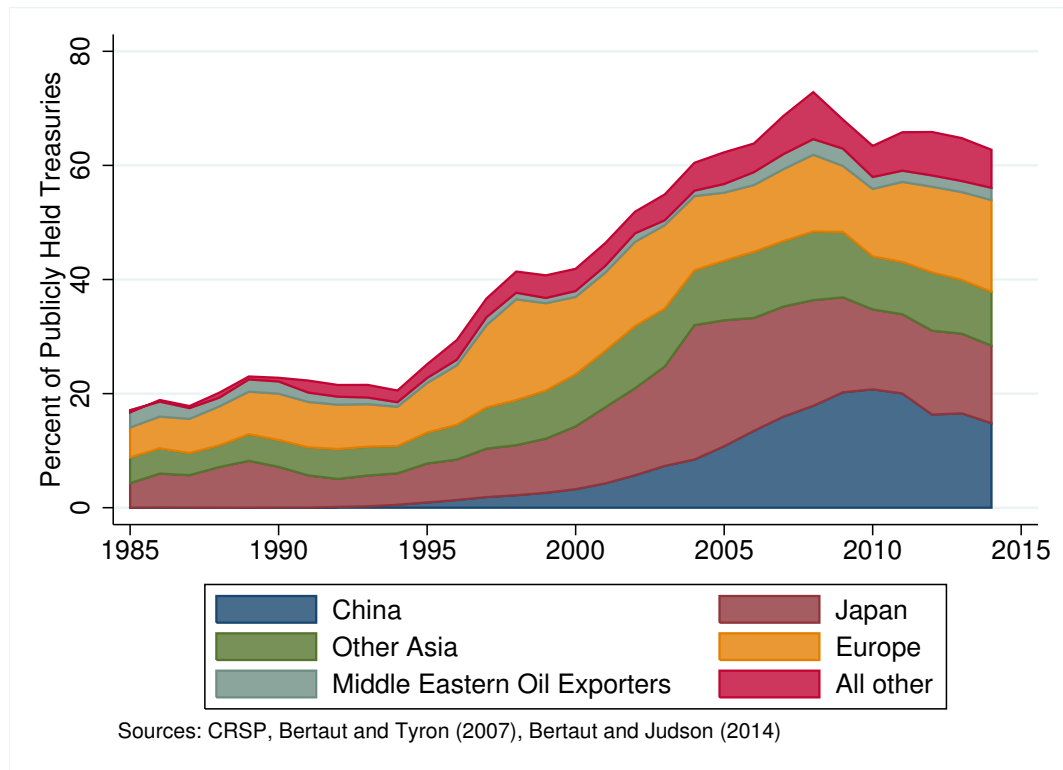
This paper asks whether the massive acquisition of U.S. Treasury securities, and recent offloading, by foreign official entities has altered the yield curve. Results suggest that yes, in fact, the increase in demand for Treasuries by foreign governments has shifted the entire yield curve down, with the largest effects on the 2-year yield.

This has important policy implications. If foreign officials unexpectedly sell off their sizable Treasury positions, U.S. interest rates will likely rise. Additionally, if the financial crisis was fueled by low interest rates in the early 2000s, then foreign official purchases may have been part of the story. Ironically, foreign governments bought U.S. Treasury securities to fend off one type of crisis—another Asian financial crisis—but may have contributed to a different crisis—the global financial crisis.

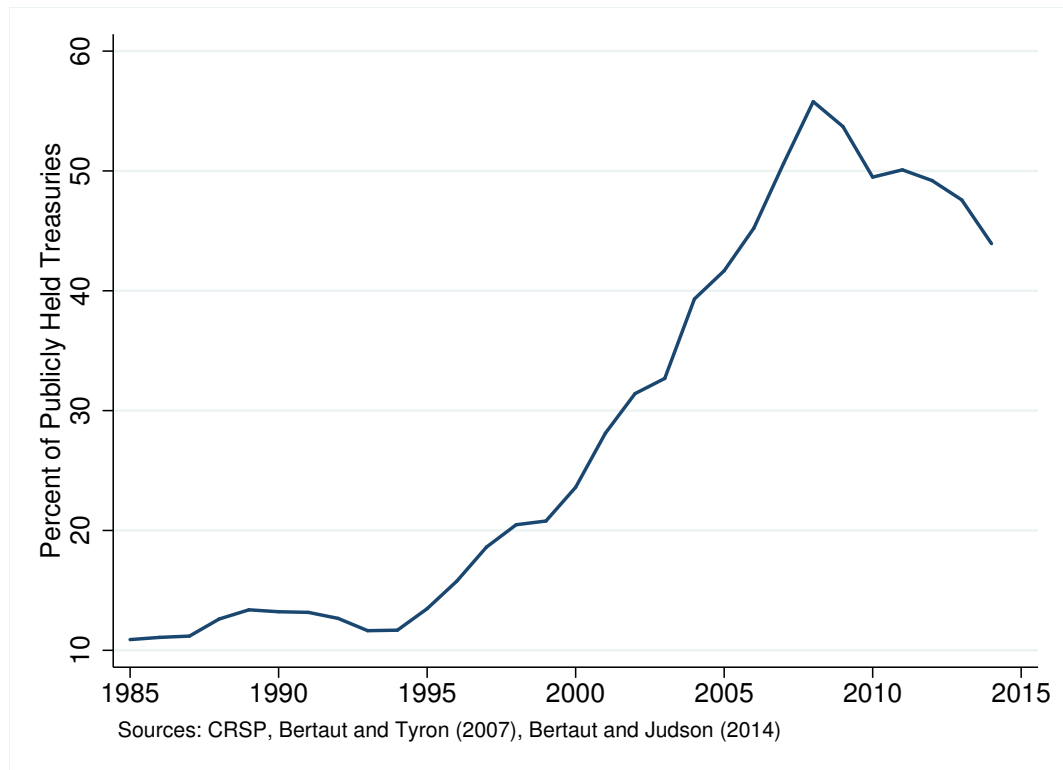
Chapter 1 is currently being prepared for submission for publication; Erin L. Wolcott. The dissertation author was the principal author on this paper.



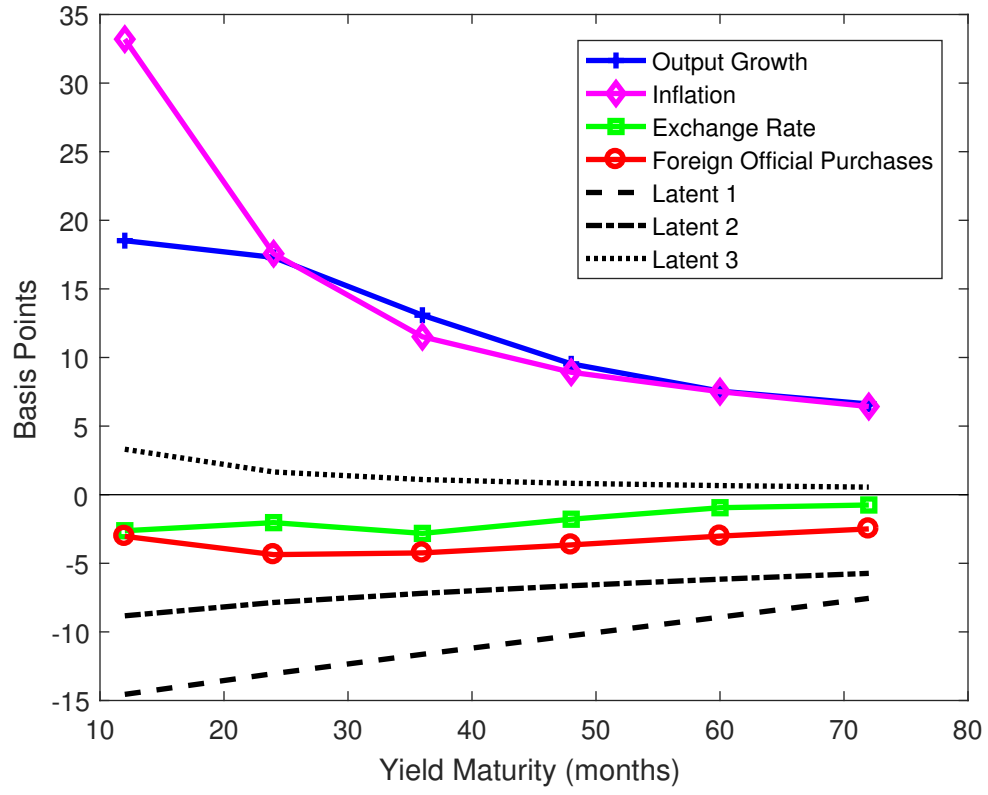
**Figure 1.1:** Global Foreign Exchange Reserves



**Figure 1.2:** Percent of Treasuries Held by Foreigners



**Figure 1.3:** Percent of Treasuries Held by Foreign Governments



**Figure 1.4:** Factor Loadings

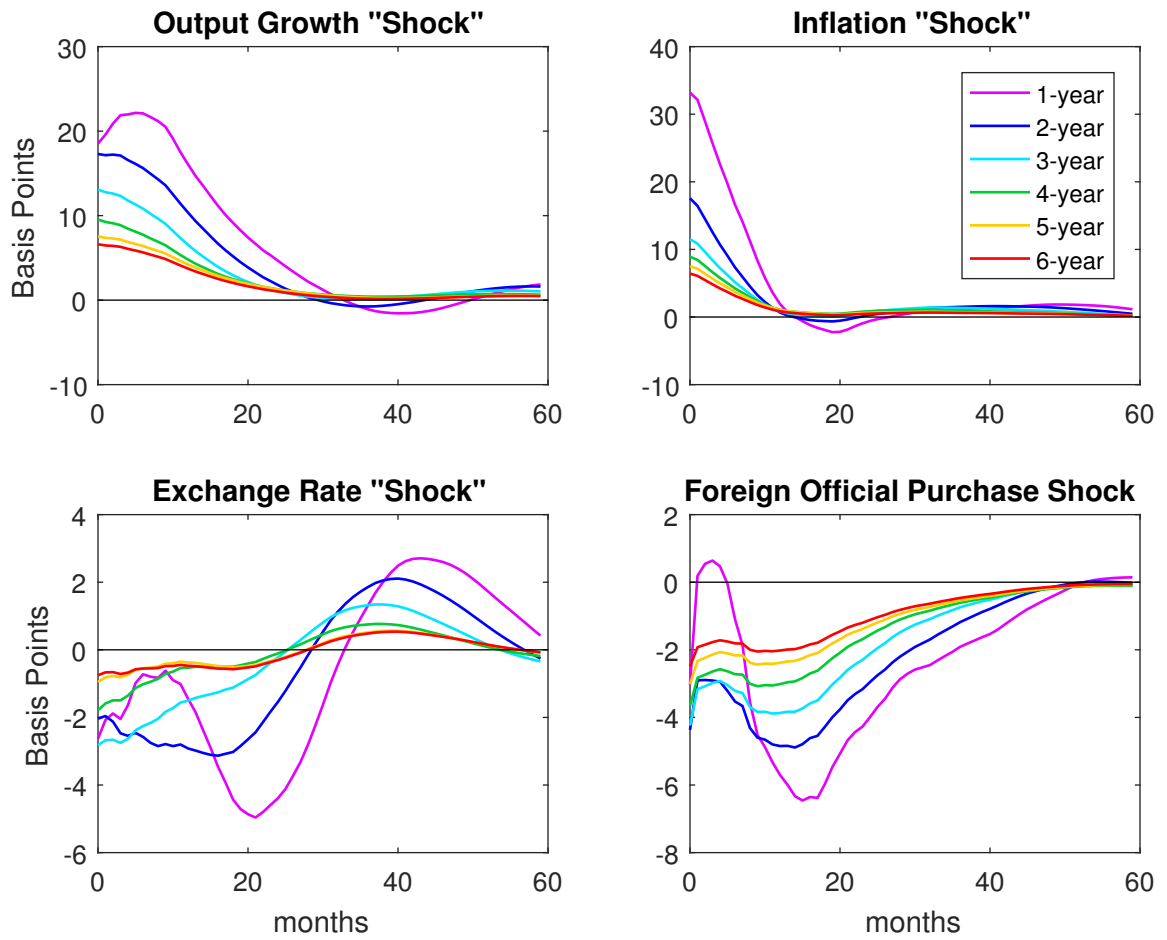
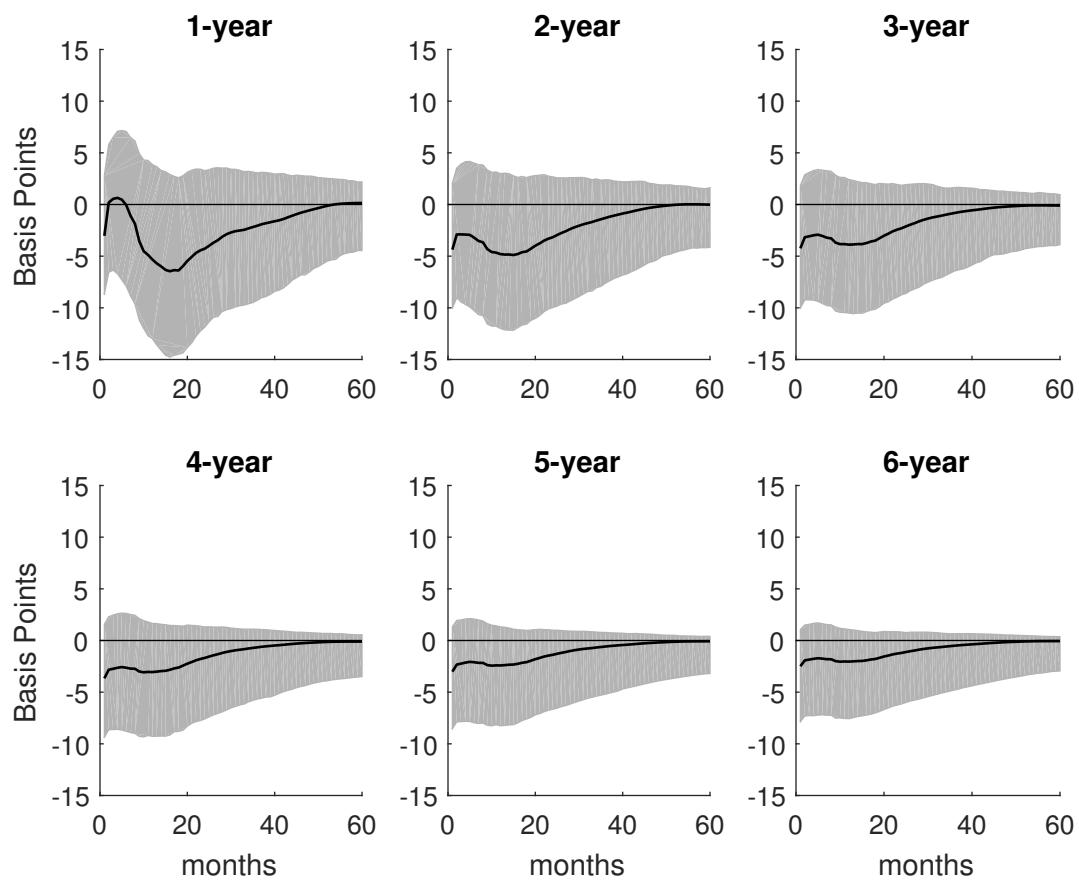
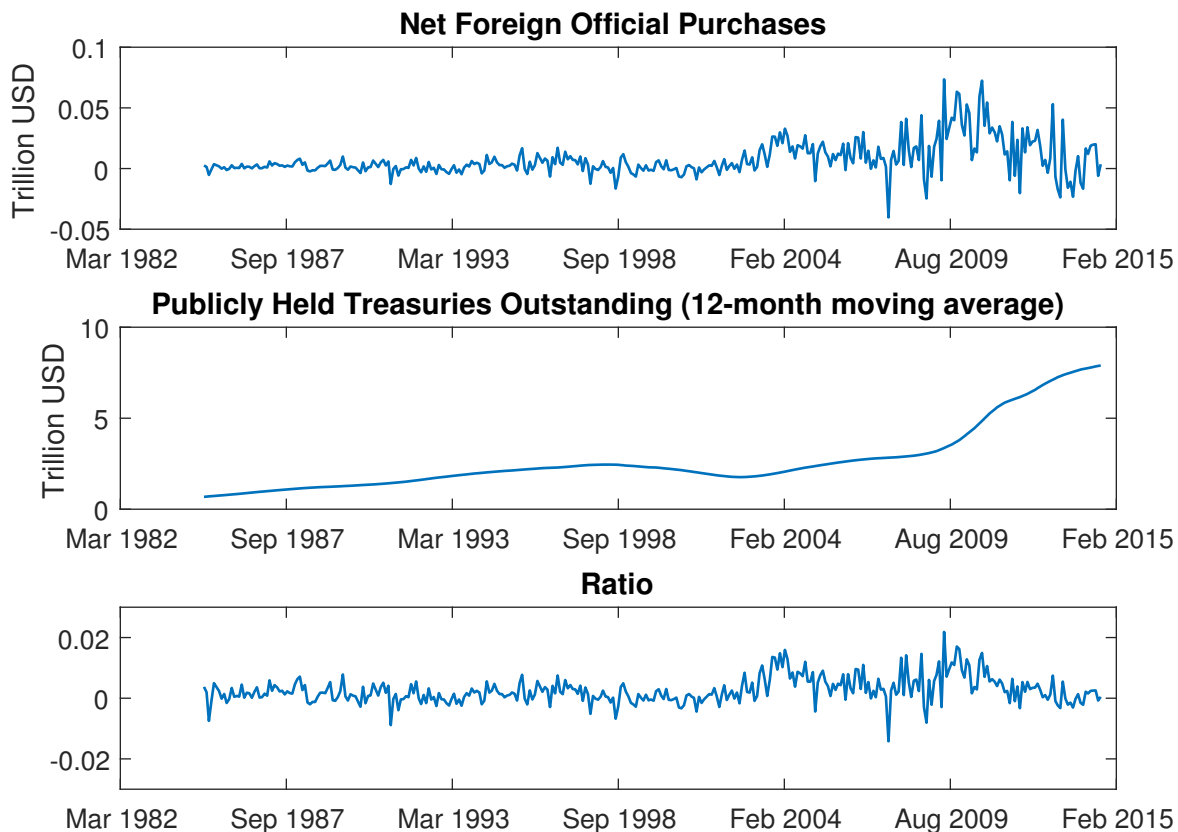


Figure 1.5: Impulse Responses of Yields



**Figure 1.6:** Response of Yields to Foreign Official Purchase Shock <sup>14</sup>

## 1.9 Appendix: Stationary Variable



**Figure 1.7:** Scaling Net Foreign Official Purchases by Treasuries Outstanding

The first panel of Figure 1.7 plots net Treasury purchases by foreign governments from Bertaut and Tryon (2007) and Bertaut and Judson (2014). To obtain a stationary variable, I follow Beltran et al. (2013) and scale net foreign official purchases by publicly held Treasuries outstanding (the second panel of Figure 1.7). The third panel, entitled “Ratio” plots the scaled foreign official purchase variable, as used in the analysis. Comparing panel 1 to panel 3, the latter appears more stationary.



## 1.10 Appendix: Parameter Mapping

The mapping between structural and reduced-form parameters follows:

$$\begin{aligned}
\Phi_{mm}^* &= [\rho_1 \ \rho_2 \ \dots \ \rho_{12}] \\
A_1^* &= A_1 - B_{1\ell} \rho_{\ell\ell} B_{1\ell}^{-1} A_1 \\
\Phi_{1m}^* &= \begin{bmatrix} B_{1m}^{(1)} & 0 \end{bmatrix} - B_{1\ell} \rho_{\ell\ell} B_{1\ell}^{-1} \begin{bmatrix} B_{1m}^{(0)} & B_{1m}^{(1)} \end{bmatrix} \\
\Phi_{11}^* &= B_{1\ell} \rho_{\ell\ell} B_{1\ell}^{-1} \\
\Psi_{1m}^* &= B_{1m}^{(0)} \\
A_2^* &= A_2 - B_{2\ell} B_{1\ell}^{-1} A_1 \\
\Phi_{2m}^* &= B_{2m} - B_{2\ell} B_{1\ell}^{-1} B_{1m} \\
\Phi_{21}^* &= B_{2\ell} B_{1\ell}^{-1} \\
\text{Var} \begin{bmatrix} u_{mt}^* \\ u_{1t}^* \\ u_{2t}^* \end{bmatrix} &= \begin{bmatrix} \Omega_m^* & 0 & 0 \\ 0 & \Omega_1^* & 0 \\ 0 & 0 & \Omega_2^* \end{bmatrix} = \begin{bmatrix} \Sigma_{mm} \Sigma'_{mm} & 0 & 0 \\ 0 & B_{1\ell} B'_{1\ell} & 0 \\ 0 & 0 & \Sigma_e \Sigma'_e \end{bmatrix},
\end{aligned}$$

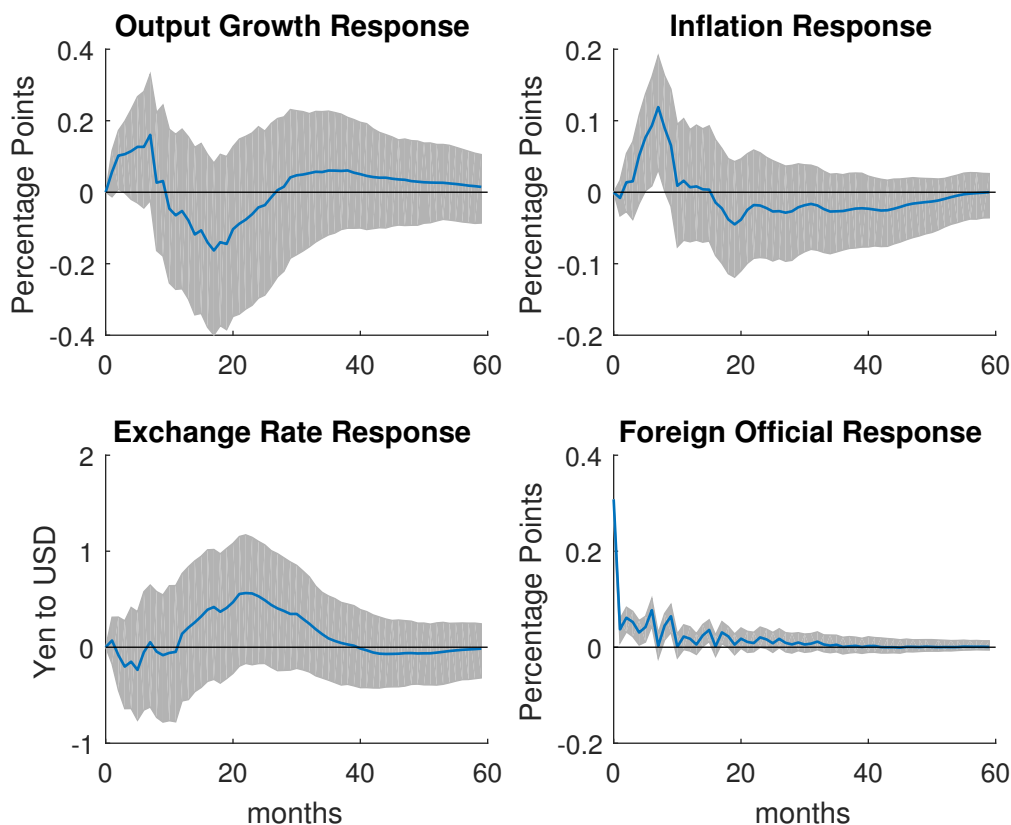
where  $\hat{\Sigma}_{mm}$  is the Cholesky factorization of  $\hat{\Omega}_m^*$  and  $\hat{\Sigma}_e$  is the square root of the diagonal elements of  $\hat{\Omega}_2^*$ .<sup>15</sup> Additionally,  $A_1, A_2, B_1, B_2$  are defined as:

$$\begin{bmatrix} A_1 \\ A_2 \end{bmatrix} = \begin{bmatrix} \alpha_3 \\ \alpha_{12} \\ \alpha_{120} \\ \alpha_6 \\ \alpha_{24} \\ \alpha_{60} \end{bmatrix}, \quad \begin{bmatrix} B_{1m}^{(0)} & B_{1m}^{(1)} & B_{1\ell} \\ B_{2m}^{(0)} & B_{2m}^{(1)} & B_{2\ell} \end{bmatrix} = \begin{bmatrix} \beta'_3 \\ \beta'_{12} \\ \beta'_{120} \\ \beta'_6 \\ \beta'_{24} \\ \beta'_{60} \end{bmatrix},$$

where for  $i = 1, 2$ ,  $B_{im}^{(0)}$  are  $(3 \times 4)$  matrices relating the observed yields to the 4 contemporaneous macro factors.  $B_{im}^{(1)}$  are  $(3 \times 44)$  matrices relating the observed yields to 11 lags of the 4 macro factors. Lastly,  $B_{i\ell}$  are  $(3 \times 3)$  matrices relating the observed yields to the latent factors.

<sup>15</sup>Macro variables in  $f_t^m$  are ordered as follows: output growth, inflation, exchange rate, foreign official purchases scaled by publicly held Treasuries outstanding.

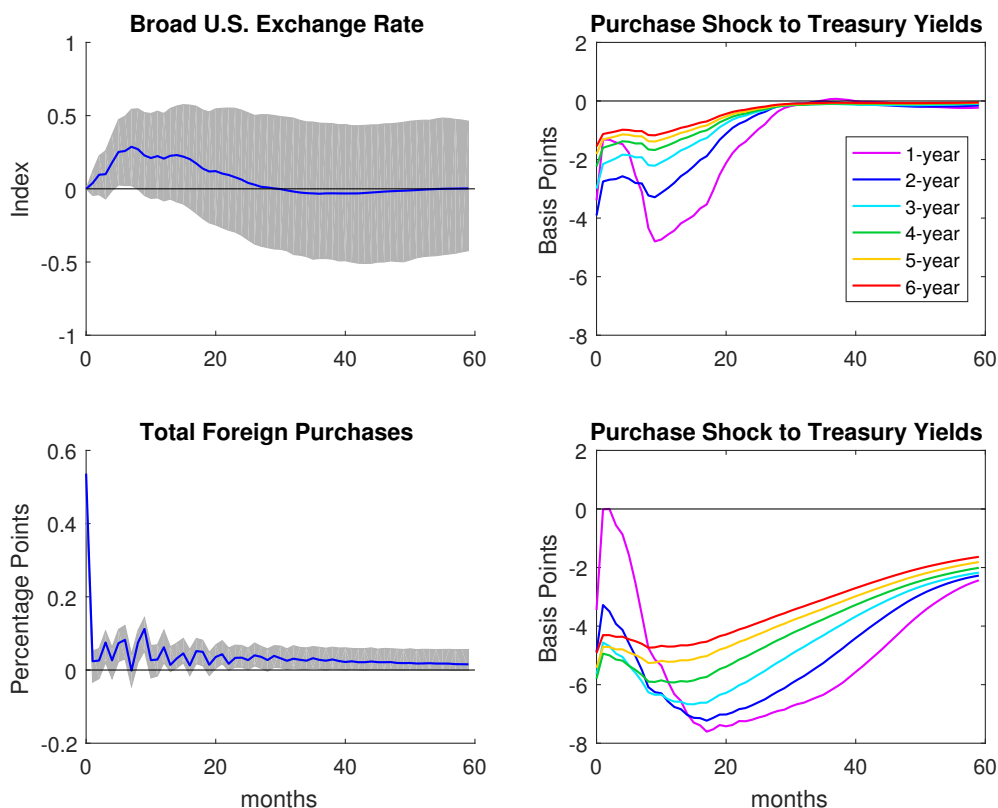
## 1.11 Appendix: Macro Variable SVAR



**Figure 1.8:** Foreign Official Purchase Shock

Figure 1.8 plots impulse response functions from a one standard deviation shock of foreign official purchases to the macro variables. In the analysis, these paths are fed into the ATSM to examine the effect on yields. Panel 1 reveals purchases of U.S. Treasuries by foreign governments are positively correlated with U.S. output growth on impact, but this relation becomes statistically indistinguishable from zero in a matter of months. Inflation in panel 2 spikes a year after the onset of a foreign official purchase shock, just as we would expect an increase in demand for U.S. assets to elevate prices. In panel 3 foreign official purchases have no robust effects on the Yen/USD exchange rate. The last panel of Figure 1.8 illustrates what a typical shock to foreign official purchases looks like. A shock is a 0.3 percentage point increase in net purchases that does not persist; purchases quickly return to zero.

## 1.12 Appendix: Alternative Macro Variables



**Figure 1.9:** Impulse Responses of Macro Variables and Implied Path for Yields

Each row of Figure 1.9 corresponds to a specification with a different set of macro variables. The top row replaces the Yen/USD exchange rate with a broad measure of the U.S. dollar as the third variable in the SVAR. This broad index, published by the Federal Reserve, is a weighted average of the foreign exchange values of the U.S. dollar against currencies of major U.S. trading partners.<sup>16</sup> The northwest panel plots the response of the broad exchange rate measure to a foreign official purchase shock and the northeast panel plots the implied path of yields. Overall, results are robust to this alternative specification.

The bottom row replaces foreign *official* purchases with *total* foreign purchases as the last variable in the SVAR. The southwest panel plots a one standard deviation shock to total foreign purchases, which is larger than that to foreign official purchases. The southeast panel plots the implied path of yields. Effects here are larger and more persistent than the baseline because foreign official purchases are a subset of total foreign purchases. Moreover, the 4-year rate instead of the 2-year rate falls the most on impact.

<sup>16</sup>[http://www.federalreserve.gov/releases/h10/summary/indexb\\_m.htm](http://www.federalreserve.gov/releases/h10/summary/indexb_m.htm)

## **Chapter 2**

# **Employment Inequality: Why Do the Low-Skilled Work Less Now?**

### **2.1 Abstract**

Low-skilled prime-age men are less likely to be employed than high-skilled prime-age men and the differential has increased since the 1970s. This paper investigates why. I build a labor search model encompassing three explanations: (1) the value of leisure for lower skilled workers increased resulting in a supply shift, (2) employment opportunities for lower skilled workers decreased, likely from skill-biased technological change and trade, resulting in a demand shift, and (3) frictions in the labor market such as search frictions and job separations increased for lower skilled workers. I augment the model with heterogeneous workers and occupational choice, and calibrate the model to match a novel stylized fact: labor market tightness by skill. This stylized fact, along with data on wages and worker flows, enables me to separately identify effects of the three mechanisms listed above. I find a demand shift and job separations are the main drivers of employment inequality, while a supply shift had no robust effects, and search frictions

actually reduced employment inequality since the 1970s.

## 2.2 Introduction

Low-skilled prime-age men are less likely to be employed today than high-skilled prime-age men. This gap emerged 50 years ago and has been growing ever since. Figure 2.1 illustrates this phenomenon by plotting employment-population ratios of two educational groups: prime-age men with a high school degree or less in red (which I will refer to as low-skilled) and prime-age men with one year of college or more in blue (which I will refer to as high-skilled). In 1950 both groups had an employment rate of approximately 90 percent. In the subsequent decades employment rates of both groups declined, while the spread increased. Understanding why these patterns emerged informs us about what types of policy, if any, are appropriate. This paper builds and calibrates a labor search model to decompose the different drivers behind diverging employment rates. I find a demand shift and job separations account for the rise in employment inequality.

I develop a framework which includes three key reasons why lower skilled workers are less likely to be employed: (1) the value of leisure for lower skilled workers increased resulting in a supply shift, (2) employment opportunities for lower skilled workers decreased, likely from skill-biased technological change (SBTC) and trade resulting in a demand shift, and (3) frictions in the labor market such as search frictions and job separations for lower skilled workers increased. Depending on which mechanism widens the employment gap, policy implications will differ. For example, if reason (1) dominates, then low-skilled men's reservation wages increased relative to their offer wages. This may be a function of government transfer programs, like a rise in the number of households on disability insurance, or an exogenous increase in leisure enjoyment. Especially in the latter case, it is not clear policy should respond. In contrast, if reason

(2) or (3) dominates, there is a substantial role for policy. In the case of reason (2), low-skilled men's offer wages fell relative to their reservation wages, which is likely a function of automation technology and competition from abroad. Training programs or policies promoting demand for low-skilled workers may help. In the case of reason (3), there is some friction preventing low-skilled workers from finding jobs (which I will also refer to as matching efficiency) or driving low-skilled workers to separate from employment. Policy aimed at mitigating information or geographical frictions, or supporting unions may be the optimal response. The goal of this paper is to uncover why employment rates have diverged, so we can better understand the appropriate policy response.<sup>1 2</sup>

The paper has three contributions. The first contribution is empirical. I document a novel stylized fact: tightness (the ratio of job openings to job-seekers) between high- and low-skilled labor markets has diverged since the 1970s. This empirical finding is vital for estimation because by calibrating the model to match it, I separately identify the importance of search frictions or matching efficiency from the other channels. I combine several data sources to construct measures of labor market tightness for two peaks of the business cycle: 1979 and 2007. I find the low-skilled labor market was slightly tighter than the high-skilled market in 1979, while the high-skilled labor market was substantially tighter than the low-skilled market in 2007. This suggests there is relatively more slack in the low-skilled labor market recently than 30 years prior.

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<sup>1</sup>Other papers study the long-term decline of aggregate employment rates, rather than the divergence. For example, Elsby and Shapiro (2012) find returns to experience can theoretically generate declining employment and productivity. Yet, other papers study shorter term trends in employment rates, such as developments after the Great Recession or since 2000. For example, see Moffitt (2012), Autor and Dorn (2013), Autor, Dorn, and Hanson (2013), Aaronson et al. (2014), Acemoglu et al. (2016), and Pierce and Schott (2016).

<sup>2</sup>Cortes, Jaimovich, and Siu (2016) and the Council of Economic Advisors' 2016 Economic Report of the President find demographic changes cannot account for the decline in low-skilled employment or labor force participation. The CEA report also rules out a working spouse or other household member as an explanation because the share of prime-age men out of the labor force with a working household member is small and has declined over time. I exclude composition changes and other household income as possible channels.

The second contribution is theoretical. I build a search and matching model in the spirit of Diamond (1982), Mortensen (1982), and Pissarides (1985) (DMP henceforth) to quantify the reasons why low-skilled employment rates have been on the decline. Given the first part of the paper documents the persistent coexistence of job openings and job-seekers, it is vital the model allows for both job openings and job-seekers to coexist in equilibrium. DMP models do just that by including a friction between firms searching for employees and workers searching for jobs. I adapt the standard model in three ways: (A) workers have heterogeneous ability; (B) workers choose to search for jobs requiring either low-skilled or high-skilled tasks, where ability is only relevant in jobs requiring the latter; and (C) technology or competition from abroad differentially complements low- and high-skilled labor, which I refer to as SBTC and trade. I incorporate heterogeneity in worker ability and occupational choice because selection is part of the employment inequality story—as more men attend college, the ability composition of the college and non-college job market changes.<sup>3</sup> Ability here can also be interpreted as some other permanent characteristic acting as a barrier to college, such as family wealth or access to student loans. In addition, I augment the model to include a channel for demand-side effects of SBTC and trade. Note, the standard DMP model already includes parameters representing workers' value of non-market activity and labor market frictions. To summarize, the model in this paper is flexible enough to allow for three broad channels to influence differential employment trends, and for agents to respond accordingly.

The final contribution is quantitative. I calibrate two steady states to understand how the value of leisure, technology/trade, and labor market frictions impacted employment rates in the 1970s and 2000s. Specifically, I target job finding rates and labor market tightness to identify dispersion in matching efficiency across low- and high-skilled jobs.

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<sup>3</sup>In the 1970s approximately 40 percent of prime-age men had some college experience, while in the 2000s over 50 percent had some college experience.

I take job separations directly from the data.<sup>4</sup> Finally, I target wages and labor market tightness to identify changes in the value of leisure from SBTC and trade. I find a demand shift and job separations are the main drivers of employment inequality, while a supply shift had no robust effects, and matching efficiency actually reduced employment inequality since the 1970s. Through the lens of the model, the increase in high-skilled labor market tightness, together with a constant gap in job finding rates, implies the high-skilled market became less efficient at matching job-seekers with job openings, relative to the low-skilled market. Moreover, the extent of the widening wage gap implies demand for high-skilled labor increased relative to that for low-skilled labor.

This paper provides a unified framework to quantify how multiple channels contribute to employment inequality. In contrast, previous papers have focused on a single mechanism. For example, several papers postulate an increase in low-skilled workers' value of leisure is an important driver of differential employment trends. Aguiar and Hurst (2008) examine time-use data and find in 1985 nonemployed men with 12 years of education or less had 1.3 more hours of leisure, after adjusting for demographics, than men with more education.<sup>5</sup> In the 2000s this difference increased to a striking 9.7 hours. Aguiar and Hurst (2008) conclude "The results documented in this paper suggest heterogeneity in the relative value of market goods and free time—and the consequent effects on human capital and wages—may be a fruitful framework to understand income inequality." One caveat with this hypothesis is less educated workers may have more leisure because they *cannot find work*, not because they *prefer not to work*, and this descriptive approach does not necessarily distinguish between the two. Barnichon and

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<sup>4</sup>When calibrating the model, I use matched-CPS data from Nekarda (2009) to construct job finding and separation rates. Figure 2.1 plots employment rates using the matched-CPS (dashed) and Census (solid). These two datasets do not perfectly line up because (1) the pool of respondents followed for at least two consecutive months in the matched-CPS is systematically different from the total pool of respondents in the Census, and (2) one series is demographically adjusted and the other is not.

<sup>5</sup>Aguiar and Hurst (2008) define leisure as activity excluding non-market work, child care, home production, medical care, and religious/civic duties.



Figura (2015a) attempt to isolate the supply shift channel by looking at the share of nonparticipants who answered “yes” to wanting work. They find the share of work-wanting individuals declined in the late 1990s, most severely for prime-age females. Lastly, Case and Deaton (2017) and Krueger (2016) highlight the role of health issues as barriers to work, particularly among the less educated. Mortality and morbidity rates for non-hispanic white Americans without a college degree have increased, while rates for those with a college degree have decreased. Nearly half of prime-age men who are out of the labor force have a serious health condition and take pain medication on a daily basis. My approach differs from these papers by calibrating a structural model to quantify the importance of non-market activity, relative to other channels, in accounting for the growing employment rate gap.

Other studies focus on understanding how a demand shift has differentially impacted employment rates using wage data. For example, Autor, Katz, and Krueger (1998) find despite the threefold increase in the employment share of college graduates from 1950 to 1996, in order to reconcile the widening wage gap, demand for college workers must have increased substantially. Figure 2.2 illustrates the severity of the wage gap by plotting real hourly earnings for college and non-college workers.<sup>6</sup> Other papers have similarly pointed out growing wage inequality is more consistent with a demand-side explanation than a supply-side one. See Katz (2000) for a review. More recently, Cortes, Jaimovich, and Siu (2016) consider the role of automation, defined as information and computation technology, in the decline of middle-skilled employment. Calibrating a neoclassical model featuring endogenous participation and occupational choice with this

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<sup>6</sup>I calculate real hourly earnings by dividing pre-tax wage and salary income by the number of weeks worked and the usual number of hours worked in a given week from the preceding calendar year. I exclude respondents who had no wage or salary income, who did not work a single week, or who usually worked zero hours per week last year. Although, an imperfect measure due to recall bias, this approach provides a rough estimate of hourly earnings. I scale this measure by the Consumer Price Index to convert to real hourly earnings. I test robustness to excluding respondents who worked less than 50 weeks per year and less than 35 hours per week under the presumption recall bias may be stronger among part-time workers with more flexible schedules. Nevertheless, real hourly earnings are robust.

narrow definition of technological change cannot account for the employment rate trends we observe in the data.

Finally, there is a long-standing literature studying matching efficiency, an important labor market friction (Lipsey (1966); Abraham and Wachter (1987); Blanchard and Diamond (1989)). More recently, the focus has been on explaining the decline in matching efficiency during and after the Great Recession (Barnichon et al. (2012); Davis, Faberman, and Haltiwanger (2013); Şahin et al. (2014); Hall and Schulhofer-Wohl (2015); Herz and Van Rens (2015); Barnichon and Figura (2015b); Hornstein and Kudlyak (2016)). I look over a longer period and ask how relative matching efficiency across skill groups has evolved. *A priori* the direction is unclear. If high-skilled workers are more likely to use online job posting boards, thereby increasing their matching efficiency, this would widen the employment rate gap.<sup>7</sup> However, if high-skilled jobs have become more specialized, possibly reducing efficiency, or the platform economy such as Uber has increased low-skilled efficiency, this would close the employment rate gap. I find the latter explanation is more likely: matching efficiency declined for college workers and increased for non-college workers between 1979 and 2007.

The paper is organized as follows: Section 2.3 documents the novel stylized fact regarding labor market tightness; Section 2.4 outlines the structural framework and steady state implications; Section 2.5 details how I disentangle effects of the three channels; Section 2.6 presents results of the calibration for two business cycle peaks: 1979 and 2007; lastly, Section 2.7 concludes.

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<sup>7</sup>Faberman and Kudlyak (2016) find the share of job-seekers with a bachelor's degree or more on Snagajob (an online job posting board) is nearly twice as large as the share of unemployed workers with a Bachelor's degree or more in the CPS.

## 2.3 Empirical Findings

This section documents a novel stylized fact: the market for low-skilled labor has more slack than the market for high-skilled labor today, which was not the case in the late 1970s. By calibrating the model to match this empirical finding, I can distinguish how three potential mechanisms influence employment inequality.

### 2.3.1 Labor Market Tightness Definition

The standard definition of labor market tightness, which I denote  $\theta_j^u$ , uses unemployment in the denominator:

$$\theta_j^u \equiv \frac{V_j}{U_j},$$

where the numerator is the number of job vacancies and the denominator is the number of unemployed individuals. In this context, tightness is disaggregated by skill where  $j \in \{L, H\}$ . Specifically,  $V_L$  is the number of vacancies for low-skilled, non-college positions and  $U_L$  is the number of unemployed prime-age men without college experience. Similarly,  $V_H$  is the number of vacancies for high-skilled, college positions and  $U_H$  is the number of unemployed prime-age men with college experience. The intuition is as follows. If  $\theta_j^u$  is large, there are many vacancies for every unemployed worker. If  $\theta_j^u$  is small, there are relatively few vacancies for every unemployed worker. Thus, we expect job finding rates to generally increase with labor market tightness.

For simplification purposes, agents in my model can only have one of two labor market statuses: employed or nonemployed. In other words, I group unemployed men with men who are out of the labor force. While unemployment and nonparticipation are distinct labor market statuses over the business cycle, Elsby and Shapiro (2012) and Juhn, Murphy, and Topel (1991, 2002) argue the boundary is blurred over the long-run. At low frequencies, unemployed men resemble nonparticipants because they have relatively

long spells of joblessness and minimal employment opportunities. Moreover, the number of nonparticipants who transition to employment is greater than the number of unemployed who transition to employment in a given month (Fallick and Fleischman (2004), Hornstein, Kudlyak, and Lange (2014)). For these reasons the baseline measure of labor market tightness in this paper, which I denote  $\theta_j^n$ , uses nonemployment in the denominator, although I test robustness to the more standard unemployment measure. I restrict attention to men, ages 25-54, because men's labor force participation decisions have been historically less complex than women's. Specifically, the baseline nonemployment measure defines labor market tightness as:

$$\theta_j^n \equiv \frac{V_j}{U_j + NLF_j},$$

for  $j \in \{L, H\}$ , where  $NLF_L$  is the number of prime-age men not in the labor force with no college experience and  $NLF_H$  is the number of prime-age men not in the labor force with college experience.

Lastly, I calculate the tightness gap, which is a useful statistic illustrating how relative tightness between high- and low-skilled labor markets has evolved:

$$\text{Tightness Gap}^m = 100 \times \frac{\theta_H^m - \theta_L^m}{\theta_L^m},$$

where  $m \in \{u, n\}$  is the type of tightness measure used to construct the gap, namely the unemployment measure or nonemployment measure.

### 2.3.2 Data

I use three datasets to create measures of market tightness by skill for the 1970s and 2000s: (1) the BLS 1979 job openings pilot program, (2) data constructed by Hobijn

(2012), and (3) the Integrated Public Use Microdata Survey (IPUMS-CPS).

**BLS Pilot Program.** In order to classify job openings as high-skilled or low-skilled, I use data disaggregated by occupation. Occupations group jobs based on the task or skill content of their employees, which unlike industries group jobs based on the product category of their output. Thus, occupations are a better dimension along which to divide vacancies into high- and low-skilled. Unfortunately, U.S. vacancy data by occupation is difficult to come by due to its costly collection procedure.<sup>8</sup> To my knowledge, the only comprehensive national vacancy datasets disaggregated by occupation are The Conference Board's Help-Wanted Online (HWOL) and Hobijn (2012)'s constructed series, both of which start in the second quarter of 2005. Fortunately, in 1979 the BLS conducted a pilot study to analyze the feasibility of collecting detailed vacancy data. The pilot surveyed 465 establishments for six consecutive quarters throughout four states: Florida, Massachusetts, Texas, and Utah.<sup>9</sup> Occupational detail was collected for 19 occupations, which are based on the 1977 Standard Occupation Classification (SOC) system. Appendix 2.8 lists these occupations. I convert occupational codes to the 1970 Census system using an archived crosswalk published by the National Crosswalk Service Center.<sup>10</sup> This conversion allows me to merge vacancy data with employment data from the CPS.

**Hobijn (2012) Data.** Hobijn (2012) uses state establishment surveys covering about 10 percent of U.S. payrolls and the labor force to construct nationally representative series of job openings by occupation. Thirteen states have conducted job vacancy surveys at least once over the period 2005 to 2013. Hobijn (2012) merges this data with vacancies by industry from the Job Openings and Labor Turnover Survey (JOLTS) and data on

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<sup>8</sup>Unlike industries, where vacancies from a single firm have the same classification, occupations require firms to list openings by occupation when filling out a job openings survey.

<sup>9</sup>Plunkert (1981) publishes a subset of this data, which includes 1979Q1-1979Q3 for Florida, Massachusetts, and Texas, and 1979Q1-1979Q2 for Utah. According to the BLS, records of the remaining data no longer exist.

<sup>10</sup><http://www.xwalkcenter.org/index.php/classifications/crosswalks>

employment shares from the CPS to construct his series. Data is the monthly average over the second quarter of each year and lists occupations by 2010 2-digit SOC codes. Appendix 2.8 lists these occupations. I convert occupational codes to the 2000 Census system using a crosswalk published by the National Crosswalk Service Center.<sup>11</sup> This conversion allows me to merge vacancy data with employment data from the CPS.

**CPS Micro Data.** Individual-level data on employment status and college attainment is from the Integrated Public Use Microdata Series, version 4.0 (Flood et al. (2015)). Monthly observations for a nationally representative sample of the U.S. population start in 1976. I classify individuals who have completed at least one year of college as high-skilled, and the remaining individuals as low-skilled.

In order to construct tightness ratios by two broad categories of skill, I need to classify vacancies as either high- or low-skilled to coincide with nonemployed workers who are designated high- and low-skilled. I do this by defining  $z$  as the share of individuals with at least one year of college who are employed in a given occupation. I then choose a cutoff  $z^*$  to define high-skilled vacancies. For example, let occupations where more than sixty percent ( $z^* = 0.6$ ) of the workforce has one year or more of college experience be classified as high-skilled jobs. I check robustness to various cutoffs. Figure 2.4 plots tightness gaps where cutoff  $z^*$  ranges from 50% to 80%. For the baseline cutoff  $z^* = 0.6$ , Appendix 2.8 lists which occupations in the 1979 BLS pilot and Hobijn (2012) data are categorized as high- and low-skilled.

### 2.3.3 Labor Market Tightness Measure

Figure 2.3 plots the monthly average of job openings (red) and number of nonemployed prime-age men (blue) by low- and high-skilled in 1979 and 2007. Vacancies are categorized as high-skilled if more than 60% of employees in an occupation have

<sup>11</sup><http://www.workforceinfodb.org/ftp/download/xwalks>

at least one-year of college ( $z^* = 0.6$ ). Nonemployed men are split into two categories: unemployed (dark blue) and out of the labor force (light blue). The vertical axis is the number of nonemployed workers or vacancies in thousands. Magnitudes differ drastically across the two panels because in 1979 data is only available for four states, while in 2007 data is only available for the entire U.S. The nonemployment measures of labor market tightness, as reported in Table 2.1, are simply the red bars divided by the total blue bars. The unemployment measures in Table 2.1 are the red bars divided by the dark blue bars.

Turning to the top panel of Figure 2.3, in 1979 the number of nonemployed men exceeds the number of vacancies in both markets. However, the non-college market is tighter—there are 0.73 vacancies for every nonemployed non-college male, while there are only 0.44 vacancies for every nonemployed college male. Turning to the bottom panel, in 2007 the number of college vacancies almost equals the number of nonemployed college males. Moreover, the college market is much tighter than the non-college market—there is approximately one vacancy for every nonemployed college male, and only 0.37 vacancies for every nonemployed non-college male. From the perspective of firms, in 1979 the college market had more slack, but in 2007 the non-college market had more slack. Table 2.1 calculates the tightness gaps. In 1979 the market for college workers had 40% more *slack* than that for non-college workers, but in 2007 the market for college workers was 177% *tighter*. In recent decades firms have wanted to hire college-educated workers, but there are relatively few college-educated prime-age men who do not already have a job.

These same patterns of relative tightness hold if we use the unemployment measure of labor market tightness. Restricting attention to the dark blue bars in Figure 2.3, we see the low-skilled labor market was tighter in 1979 and the high-skilled market was tighter in 2007. This is because changes in tightness were primarily being driven by changes in vacancy postings, not the number of job-seekers. The potential concern in

using a measure of tightness with nonemployment in the denominator regards being able to separately identify matching efficiency from workers' value of leisure. If nonemployed individuals on average search less intensely than unemployed individuals because they have a higher reservation wage, the non-standard measure would attribute value of leisure to market slack. In practice, this is not a concern because relative tightness is comparable across the two measures. The tightness gap using unemployed men in 1979 was -55% and in 2007 was 136%, which is comparable to -40% and 177%, respectively. I use the nonemployment measure in this analysis because it drastically simplifies the model.

Appendix 2.11 checks robustness to using *unemployed* men and *women* in the denominator of the market tightness measure and shows the tightness gap is similar to baseline. If women's participation in the labor force is skewed towards the college job market as Cortes and Jaimovich (2016) suggest, this may drive college vacancy creation and overestimate the baseline tightness gap. I am able to rule out this potential bias because tightness gaps using unemployed men and women are similar to both measures reported in Table 2.1. Additionally, Appendix 2.17 shows estimates of matching efficiency are robust to this alternative measure.

Since we only observe labor market tightness for four states, the 1979 tightness gap may not be nationally representative, even though the BLS strategically chose a diverse set of states. Appendix 2.9 lists the tightness gap separately for each state. The tightness gap remains negative for this diverse set of states, suggesting the negative gap in 1979 was not a product of state idiosyncrasies. Another concern is that data for three months of one year may not accurately reflect the tightness gap for an entire decade. This is a limitation of the data, however, Appendix 2.10 shows the tightness gap remained above 100% throughout the 2000s despite the large business cycle (the Great Recession). This suggests the tightness gap is at least twofold larger today than it was in the 1970s, regardless of cyclical fluctuations.



Another concern is the magnitudes in Figure 2.3 are a function of the criterion classifying vacancies as either college or non-college. Figure 2.4 illustrates the percent gap between high-skilled, college market tightness ( $\theta_H^c$ ) and low-skilled, non-college market tightness ( $\theta_L^c$ ) of varying education cutoffs. The horizontal axis lists cutoffs for the share of college employment defining a high-skilled vacancy. The vertical axis is the tightness gap between high- and low-skilled jobs. Red plots the tightness gap in 1979 and blue plots the tightness gap in 2007. The tightness gap in 2007 always exceeds that in 1979, regardless of how a high-skilled vacancy is defined. Note, Figure 2.4 plots tightness gaps using the nonemployment measure of labor market tightness. Appendix 2.11 plots tightness gaps using the unemployment measure including women, which looks remarkably similar to Figure 2.4.

Overall, this section finds differential market tightness, disfavoring low-skilled workers is a pervasive and robust labor market phenomenon. This type of inequality, i.e. varying labor market conditions across skill types, did not exist in the late 1970s, but today is ubiquitous.

## 2.4 Model

The goal of this section is to build a tractable model of the labor market capturing the conditions workers face when choosing an employment status and occupation. For simplicity, the model includes only two labor force statuses: employment ( $e$ ) and nonemployment ( $n$ ); and two types of occupations: low-skilled ( $L$ ) and high-skilled ( $H$ ). The low-skilled group represents jobs requiring workers with a high school degree or less, who perform routine and/or non-cognitive tasks. The high-skilled group represents jobs requiring workers with a college education, who perform analytical and cognitive tasks.

To capture the empirical observation that job openings and job seekers simul-

taneously exist, I build a DMP model, where a friction in the labor market prevents openings and job-seekers from perfectly matching up. I augment the standard model with heterogeneous worker ability and two types of occupations workers endogenously sort into. I complicate the model with these additions because empirically the composition of workers searching for low- and high-skilled jobs has changed over time. Appendix 2.12 illustrates in the 2000s the low- and high-skilled markets were both composed of lower ability workers relative to the 1980s. As such, I allow workers in my model to choose an occupation based on their ability and the economic environment. Occupational choice has important implications for employment rates because higher ability workers are generally more productive and therefore more likely to be employed. If higher ability workers are more likely to choose one occupation over another, this impacts differential employment rates. As in the data, my model predicts both markets were made up of lower ability workers in the later period.<sup>12</sup>

### 2.4.1 Environment

Time is discrete and indexed by  $t \in \{0, 1, 2, \dots, \infty\}$ .

**Workers.** Workers are heterogeneous in their ability. I consider an economy populated by  $M$  types of workers, indexed by  $x \in \{x_1 < x_2 < \dots < x_M\}$ . Ability is permanent and perfectly observable to employers and is a discrete approximation of log-normal.<sup>13</sup> I ex-ante sort workers into submarkets based on their ability. Therefore, the aggregate labor market is organized in  $M$  submarkets indexed by worker type  $x$ . In each submarket there is a measure  $M(x)$  of infinitely lived workers of type  $x$  (with

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<sup>12</sup>Beaudry, Green, and Sand (2016) and Abel, Deitz, and Su (2014) find since the early 2000s college workers are underemployed, meaning workers with a college degree work jobs not necessarily requiring a college degree. This raises concerns about college no longer being a good proxy for high-skilled labor. However, Abel and Deitz (2014) find there are still substantial positive returns to a bachelor's degree and associate's degree. This is especially true when comparing today to the 1970s.

<sup>13</sup>When calibrating the model in Section 2.5, I focus on ability deciles such that there are  $M = 10$  types of ability levels in the economy.

$\sum_x M(x) = 1$ ) either employed  $e(x) \in [0, 1]$  or nonemployed  $n(x) \in [0, 1]$ . The aggregate labor force is then  $\sum_x (e(x) + n(x))M(x) = 1$ . Each worker is endowed with one unit of labor. For simplicity, on-the-job search is ruled out. Lastly, workers have risk-neutral preferences and discount future payoffs at rate  $\beta \in (0, 1)$ .

**Firms.** The economy is also populated by an infinite mass of identical and infinitely lived employers either producing output  $y(x)$ , or posting job vacancies  $v(x)$ , to hire nonemployed workers of type  $x$ . Employers have risk-neutral preferences and also discount the future by  $\beta$ . I assume directed search such that firms target a specific submarket  $x$  to post a vacancy and only post in one submarket at a time.

**Production Technology.** There are two types of production technologies in the economy. Technology used at low-skilled ( $L$ ) occupations, where output is not a function of worker ability. Think of a conveyer belt in an assembly line which arguably complements all manufacturing workers in the same way, regardless of their underlying ability (assuming workers show up for work). The other type of technology is used at high-skilled ( $H$ ) occupations, where output is a function of worker ability. Think of a computer, which complements high ability workers well, and low ability workers to potentially a lesser degree. Put differently, a worker's ability  $x$  is irrelevant when matched with a low-skilled job and operative when matched with a high-skilled job. Output produced by low- and high-skilled technologies is perfectly substitutable. The occupation-specific production function per worker is:

$$y_{jt}(x) = \begin{cases} A_L & \text{if } j = L \\ A_H x & \text{if } j = H \end{cases}$$

Here, labor-augmenting technology for low-skilled jobs equals  $A_L$  regardless of underlying ability, while labor-augmenting technology for high-skilled jobs,  $A_H$ , interacts with ability  $x$ . Changes in  $A_L$  and  $A_H$  represent shifts in demand, such as SBTC and competi-

tion from abroad. For instance, a decrease in  $A_L$  resembles machines and trade replacing low-skilled workers, while an increase in  $A_H$  resembles computers and communication technology increasing high-skilled workers' productivity.

**Matching Technology.** Markets are frictional. In each submarket  $x$ , there exist two constant returns to scale matching technologies:

$$m_{jt}(n_t(x), v_t(x)) = \phi_j n_t(x)^\alpha v_t(x)^{1-\alpha}, \quad (2.1)$$

where  $\alpha \in (0, 1)$  and  $\phi_j$  is matching efficiency in the low- or high-skilled market. Changes in  $\phi_j$  represent shifts in search frictions. Let  $\theta_t(x) = \frac{v_t(x)}{n_t(x)}$  denote market tightness in submarket  $x$  at time  $t$ . The job finding rate is then  $f_j(n_t(x), v_t(x)) = \frac{m_{jt}(x)}{n_t(x)} = \phi_j \theta_t(x)^{1-\alpha}$ , which I denote  $f_{jt}(\theta)$  from now on to save on notation. Similarly, the job filling rate  $q_j(n_t(x), v_{jt}(x)) = \frac{m_{jt}(x)}{v_t(x)} = \phi_j \theta_t(x)^{-\alpha}$ , which I denote  $q_{jt}(\theta)$ .

**Timing.** Employers post job vacancies and nonemployed workers search for jobs, given relative matching efficiencies, job separations, values of leisure, and productivities next period  $\{\phi_{jt+1}, \delta_{jt+t}, b_{jt+1}, A_{jt+1}\}$ . Nonemployed workers meet firms at time  $t$  and if profitable produce output at  $t + 1$ .

## 2.4.2 Equilibrium

**Firm's Problem.** Let  $V_{jt}(x)$  be the value to a firm of posting a vacancy for a worker of ability  $x$  and a job that uses either high- or low-skilled technology  $j \in \{L, H\}$  at time  $t$ . Note if the vacancy is for a low-skilled occupation  $j = L$ , ability is irrelevant.

$$V_{jt}(x) = -\kappa + \beta \left[ q_{jt}(\theta) J_{jt+1}(x) \right], \quad (2.2)$$

where  $\kappa$  is the cost of posting a vacancy.<sup>14</sup>  $J_{jt+1}(x)$  is a firm's surplus next period from matching with a worker using technology  $j$ . The value of posting a vacancy is a function of the type of technology because firm surplus depends on technology. Firm surplus this period equals:

$$J_{jt}(x) = y_{jt}(x) - \omega_{jt}(x) + \beta \left[ (1 - \delta_j) J_{jt+1}(x) \right], \quad (2.3)$$

where  $\omega_{jt}(x)$  is the endogenously determined wage paid to a worker with ability  $x$  using technology  $j$ . The occupation-specific parameter  $\delta_j$  is the exogenous separation rate. Here, all workers in their respective occupational categories separate from their job at rate  $\delta_j$ .<sup>15</sup>

**Worker's Problem.** On the worker side, the value of being matched with a job is the discounted value of retaining that match or entering the nonemployment pool next period,

$$W_{jt}(x) = \omega_{jt}(x) + \beta \left[ (1 - \delta_j) W_{jt+1}(x) + \delta_j N_{jt+1}(x) \right]. \quad (2.4)$$

The value of being nonemployed  $N_{jt}(x)$  is defined by the following condition:

$$N_{jt}(x) = \max \left[ N_{Lt}^c(x), N_{Ht}^c(x) \right], \quad (2.5)$$

where  $N_{Lt}^c(x)$  represents the continuation value of nonemployment when a worker chooses to search for low-skilled work (i.e. jobs where their ability does not matter) and  $N_{Ht}^c(x)$  represents the continuation value of nonemployment when a worker chooses to search for high-skilled work (i.e. jobs where output and therefore wages depend on ability). The recursive formulation for the continuation value of nonemployment, when an individual

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<sup>14</sup>In the baseline specification  $\kappa$  is constant across occupations, but Appendix 2.18 tests robustness to  $\kappa_H > \kappa_L$ .

<sup>15</sup>See Fujita and Ramey (2013) for an assessment of the various approaches to modeling the separation rate. For the purposes of this model, I assume an exogenous separation rate.

searches for  $j \in \{L, H\}$  type work follows:

$$N_{jt}^c(x) = b_j + \beta \left[ f_{jt}(\theta) W_{jt+1}(x) + (1 - f_{jt}(\theta)) N_{jt+1}(x) \right], \quad (2.6)$$

where  $b_j$  is the value of leisure, which varies between low- and high-skilled occupations. Changes in  $b_j$  represent shifts in labor supply. When an agent chooses to search in the low-skilled market, think of that worker as forgoing college. When an agent chooses to search in the high-skilled market, think of that worker as attending college so she can search for college jobs. Dynamically agents can switch from a high- to low- skill job. Empirically workers cannot switch from having some college experience to no college experience. Section 2.6 calibrates the model to match two steady states: 1979 and 2007, such that agents do not switch occupations in a given steady state. Agents who do switch occupations between 1979 and 2007 should be thought of as different people with the same ability level.

**Nash Bargaining.** Workers and firms in each market negotiate a contract dividing match surplus according to the Nash bargaining solution, where  $\pi \in (0, 1)$  is the worker's bargaining weight.<sup>16</sup> Total match surplus is calculated by adding up firm value  $J_{jt}(x)$  and worker value  $W_{jt}(x)$  minus values of the outside options  $V_{jt}(x)$  and  $N_{jt}(x)$ . Let  $S_{jt}(x) = \max\{J_{jt}(x) + W_{jt}(x) - V_{jt}(x) - N_{jt}(x), 0\}$  denote total match surplus in submarket  $x$  using technology  $j$ . Workers receive  $\pi S_{jt}(x)$  from a match and firms receive  $(1 - \pi) S_{jt}(x)$ .<sup>17</sup> The worker and firm will agree to continue the match if  $S_{jt}(x) > 0$ , otherwise they will separate, in which case  $S_{jt}(x) = 0$ .

**Free Entry.** To close the model I assume an infinite number of firms are free to enter each submarket and post vacancies, thereby pushing down the value of posting a

<sup>16</sup>In the baseline specification  $\pi$  is constant across occupations, but Appendix 2.18 tests robustness to  $\pi_H > \pi_L$ .

<sup>17</sup>Nash bargaining provides additional expressions representing worker and firm value of a match, such that we can set  $W_{jt}(x) - N_{jt}(x) = \pi S_{jt}(x)$  and  $J_{jt}(x) = (1 - \pi) S_{jt}(x)$ .

vacancy to zero. The free entry condition implies  $V_{jt}(x) = 0, \forall j, t, x$ .<sup>18</sup>

### 2.4.3 Steady State

The following subsection derives four expressions summarizing the steady-state equilibrium, namely the job creation curve, wages, nonemployment, and a condition representing how agents choose whether to search for a low- or high-skilled occupation. To simplify notation, let any variable  $Z_t = Z_{t+1} = Z$  for the remainder of this subsection.

**Job Creation Curve.** In steady state, combining equation (2.2), equation (2.3), and the free entry condition yields:

$$y_j(x) - \omega_j(x) - \frac{\kappa(\beta^{-1} + \delta_j - 1)}{q_j(\theta)} = 0. \quad (2.7)$$

The DMP literature refers to this expression as the job creation curve. If the firm had no hiring cost,  $\kappa$  would be zero and equation (2.7) would be the standard marginal productivity condition where marginal product equals wage. In DMP models, nonzero vacancy posting costs cut into total surplus and under Nash bargaining that cut translates into lower wages.

**Steady State Wages.** Under Nash bargaining and free entry, equations (1)-(6) endogenously determine wages:

$$\omega_j(x) = (1 - \pi)b_j + \pi(y_j(x) + \kappa\theta). \quad (2.8)$$

See Appendix 2.13 for a derivation. Workers are rewarded for helping firms save on hiring costs. Workers also enjoy a share of output and a fraction of the outside option. Wages are increasing in market tightness, and for high-skilled jobs, wages are increasing

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<sup>18</sup>For the baseline calibration, I impose the Hosios condition in each submarket ( $\alpha = \pi$ ), such that the equilibrium is optimal (i.e. the Planner's solution equals the market equilibrium).

in ability and labor-augmenting technology.

**Steady State Nonemployment.** The rate at which employed workers enter the nonemployment pool is governed by  $\delta_j$ . The flow of workers moving from employment to nonemployment in each submarket and period is then  $\delta_j(1 - n_j(x))$ . Conversely, the rate at which nonemployed workers find jobs is governed by  $f_j(\theta)$ . The flow of workers moving from nonemployment to employment in each submarket and period is then  $f_j(\theta)n_j(x)$ . In steady state the flow into employment (nonemployment) must equal the flow out of employment (nonemployment). Therefore,  $\delta_j(1 - n_j(x)) = f_j(\theta)n_j(x)$  which reduces to:

$$n_j(x) = \frac{\delta_j}{\delta_j + \phi_j \theta^{1-\alpha}}. \quad (2.9)$$

In steady state the number of nonemployed people within a given ability level is a function of the exogenous separation rate, matching efficiency, and tightness ratio. The upcoming proposition illustrates market tightness  $\theta$  is generally a function of labor-augmenting technology and ability. Therefore, employment rates vary not only over occupations, but also over ability  $x$ .

**Choosing a High- or Low-Skilled Occupation.** When in the nonemployment pool, workers endogenously choose which type of occupation they want to search for. They make this decision by maximizing over the future discounted value of both options. In steady state, this decision (i.e. equation (2.9)) becomes the following after substituting in equation (2.4):

$$\max_j N_j(x) = \max_j \left[ \frac{b_j(\beta^{-1} + \delta_j - 1) + f_j(\theta)\omega_j(\theta)}{(1 - \beta)(\beta^{-1} - 1 + f_j(\theta) + \delta_j)} \right]. \quad (2.10)$$

Equations (2.7), (2.8), (2.9) and (2.10) determine the steady-state equilibrium. Let  $x_\xi \in \{x_1 < x_2 < \dots < x_M\}$  be the highest ability (or cutoff) worker either employed



or searching for work in a low-skilled occupation.

**Balanced Growth.** This economy does not necessarily follow a balanced growth path. In other words, technology may differentially affect workers and their employment statuses. The following proposition specifies a condition sufficient for balanced growth.

**Proposition.** *If vacancy posting costs  $\kappa$  and the value of leisure  $b_j$  are directly proportional to output, then tightness  $\theta$  is constant across ability  $x$  and labor-augmenting technology  $A_j$ .*

*Proof.* Steady state tightness  $\theta$  solves:

$$y_j(A_j, x) = \theta^\alpha \kappa \left( \frac{\beta^{-1} + \delta_j - 1}{\phi_j(1 - \pi)} \right) + \theta \kappa \left( \frac{\pi}{1 - \pi} \right) + b_j. \quad (2.11)$$

Suppose  $\kappa = \tilde{\kappa}y_j$  and  $b_j = \tilde{b}_jy_j$  then equation (2.11) is not a function of  $x$  or  $A_j$ .  $\square$

Equation (2.11) is instrumental to understanding how SBTC and trade generates different employment outcomes across ability levels. Suppose vacancy posting costs and the value of leisure are both directly proportional to output. In other words, replace wherever there is a  $\kappa$  with  $\tilde{\kappa}y_j$ , and a  $b_j$  with  $\tilde{b}_jy_j$  in equation (2.11). The economic interpretations of these changes is that it is more costly for firms to post vacancies for jobs with higher output potential, and leisure is valued more by workers with higher output potential. Imposing both assumptions implies a balanced growth path, meaning equation (2.11) is no longer a function of output—because  $y_j$  can be divided out—and therefore market tightness is no longer a function of ability or labor-augmenting technology. With this setup, it would be impossible for SBTC and trade to affect tightness and therefore the employment gap. Thus, the model assumes non-balanced growth.

That said, the assumption for balanced growth is not entirely unfounded. Productive jobs may require more effort to find the right worker-job match relative to less

productive jobs. Unemployment benefits—which are one component of the value of leisure—in the U.S. are between 40 and 50 percent of previous pay.<sup>19</sup> However, it is unlikely *both* parameters—vacancy posting costs and value of leisure—are *directly* proportional to output. As long as at least one is not directly proportional, then market tightness is a function of output, and the employment gap will co-move with technological change and competition from abroad. In the baseline model, for simplicity, I assume neither vacancy posting costs or the value of leisure depend on output.

## 2.5 Calibration

I consider three possible mechanisms contributing to the evolving employment gap, namely, a supply shift, a demand shift, and labor market frictions, where the latter is composed of two parts: matching efficiency and job separations. How these parameters change across low- and high-skilled workers determines relative employment outcomes. I compare the 1970s to the 2000s by calibrating two steady states, one representing the 1979 business cycle peak, and the other representing the 2007 peak. There are three stages to the estimation procedure. First, I recover matching efficiency in both markets and time periods using the matching function. Second, I jointly determine value of leisure (the key supply shift parameter) and labor-augmenting technology (the key demand shift parameter) using the job creation curve and wage equation. Third, I recover the mean and standard deviation of ability levels in this economy by targeting the share of workers in the high-skilled market in 1979 and 2007. Note, for the job separations channel, I calculate separation rates directly from the data, which I discuss in Section 2.6.

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<sup>19</sup>[http://workforcesecurity.doleta.gov/unemploy/docs/repl\\_FY13.txt](http://workforcesecurity.doleta.gov/unemploy/docs/repl_FY13.txt).

### 2.5.1 Matching Efficiency

Matching technology, summarized by equation (2.1) depends on four parameters: the job finding rate  $f$ , tightness  $\theta$ , matching elasticity  $\alpha$ , and matching efficiency  $\phi$ . I have estimates for three of these four parameters, which allows me to recover matching efficiency.

Section 2.3 provides estimates of tightness in the low- and high-skilled market. I take an estimate of elasticity  $\alpha$  from the literature. Rewriting equation (2.1) depicts an expression for matching efficiency:

$$\phi_j = \frac{f_j(\theta(x))}{\theta(x)^{1-\alpha}}. \quad (2.12)$$

From the proposition in Section 2.4.3, we know market tightness is generally a function of individual ability  $x$ . Since we do not have estimates of market tightness and job finding rates by ability in the data, I aggregate over individuals within a given occupation category  $j$  for the empirical analogue of equation (2.12).<sup>20</sup> Specifically, matching efficiency estimates are calculated as:

$$\hat{\phi}_j = \frac{\hat{f}_j}{\hat{\theta}_j^{1-\alpha}}, \quad (2.13)$$

where  $\hat{f}_j$  is the empirical job finding rate and  $\hat{\theta}_j$  is the empirical market tightness measure for men without college experience  $j = L$  and men with at least some college experience  $j = H$ . I do this separately for 1979 and 2007 to recover the following set of parameters:

$$\{\hat{\phi}_{L,1979}, \hat{\phi}_{H,1979}, \hat{\phi}_{L,2007}, \hat{\phi}_{H,2007}\}.$$

<sup>20</sup>Given the functional form of the production function, tightness is only a function of ability in the high-skilled market. Since output does not vary by ability in the low-skilled market, neither does labor market tightness.

## 2.5.2 Disentangling Supply and Demand

It is a bit more involved to identify changes in the value of leisure, the supply shift parameter, from changes in labor-augmenting technology, the demand shift parameter. Equations (2.7) and (2.8) provide two equations to do this. For each period and occupation, there are two equations (a job creation curve and wage equation) and two unknown parameters (value of leisure and labor-augmenting technology.) The estimation procedure relies on simulated method of moments (SMM). For 1979, I choose an initial  $\{b_L, b_H, A_L, A_H\}$  and solve for tightness and wages using the job creation curve and wage equation. For 2007, I choose an initial  $\{b_L, b_H, A_L, A_H\}$  and likewise solve for tightness and wages. I then compare the model's generated parameters with the empirical market tightness and wage data. I minimize the squared difference to back out the true values of leisure and technology. One complication is the model produces a tightness and wage for each ability level in the high-skilled labor market, rather than an aggregate, as in the low-skilled market. Before comparing the model's tightness and wage parameters with the data, I must average over ability within the high-skilled market  $j = H$ . Specifically, I minimize the following expressions:

$$w_{T\theta} \left( \hat{\theta}_{HT} - \frac{1}{M} \sum_{x_i}^{x_M} \theta_{HT}(x) \right)^2, \quad (2.14)$$

$$w_{T\omega} \left( \hat{\omega}_{HT} - \frac{1}{M} \sum_{x_i}^{x_M} \omega_{HT}(x) \right)^2, \quad (2.15)$$

where  $\hat{\theta}_{HT}$  and  $\hat{\omega}_{HT}$  are the empirical tightness ratio and real wage of the high-skilled market in year  $T \in \{1979, 2007\}$ . Additionally,  $w_{T\theta}$  and  $w_{T\omega}$  are the weights associated with each component.<sup>21</sup>

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<sup>21</sup>I weight each component by its percent difference such that larger values of tightness or wages are not automatically given more importance.

### 2.5.3 Ability Parameters

The final set of parameters to recover are the mean  $\mu_x$  and standard deviation  $\sigma_x$  of ability. I do this by targeting the share of men with college experience. The assumption here is men who attended at least one year of college search for high-skilled, college jobs and men with less than one year of college search for low-skilled, non-college jobs. In 1979, 43% of prime-age men had at least one year of college, while in 2007, 56% had at least one year of college. Appendix 2.14 plots the time series of college share with reference lines at 1979 and 2007. Matching these moments allows me to recover  $\mu_x$  and  $\sigma_x$ .

## 2.6 Results

Table 2.2 lists the parameter estimates for 1979 and 2007, where  $z^* = 0.6$ .<sup>22</sup> The first third of the table take values from the literature. I calibrate the model to match monthly observations and accordingly set the discount rate  $\beta$  to 0.9967. The elasticity parameter  $\alpha = 0.62$  is from Veracierto (2011), which is estimated for a matching function where nonparticipants are grouped with the unemployed. Worker bargaining power follows the Hosios (1990) condition, equaling the elasticity parameter  $\pi = \alpha$ , such that the allocation of labor is efficient. It is plausible high-skilled bargaining power is greater than that of the low-skilled; Appendix 2.18 texts robustness to  $\pi_H > \pi_L$ . There is a wide range of values for vacancy posting costs in the literature. Cairo and Cajner (2013) find the ratio of average recruiting costs to average wages in a given month hovers around 0.1 regardless of education, while Gavazza, Mongey, and Violante (2016) find it is closer to 0.9. I split the difference and use 0.5.<sup>23</sup>

<sup>22</sup>Appendix 2.16 shows counterfactuals where  $z^* = 0.5$  and  $z^* = 0.65$ .

<sup>23</sup>Appendix 2.18 texts robustness to high-skilled vacancy posting costs being greater than low-skilled posting costs,  $\kappa_H > \kappa_L$ .

The second third of the table take estimates from the data. Using matched-CPS data from Nekarda (2009), I compute separation and job finding rates for men in the low- and high-skilled labor market. Appendix 2.15 plots these data by college and non-college, with reference lines at 1979 and 2007. Separation rates (employment to nonemployment) are taken directly from the data while matching efficiencies are recovered by targeting job finding rates (nonemployment to employment), as described in Section 2.5. I find matching efficiency increased for low-skilled workers from the 1970s to 2000s, while it decreased for high-skilled workers. In 1979 the high-skilled market was more efficient at linking job openings with job-seekers, while in 2007 the low-skilled market was more efficient. This fact also holds when using unemployed men and women rather than nonemployed men. Appendix 2.17 lists matching efficiency estimates for a tightness measure with unemployed men and women in the denominator and job finding rates using U-E flows for men and woman.

The last third of the table lists parameters disciplined by the model. Low- and high-skilled value of leisure both decreased between 1979 and 2007, yet high-skilled value of leisure decreased by more. Additionally, I find high-skilled workers value non-market activity more than low-skilled workers, which is consistent with higher paid workers having higher reservation wages. Low-skilled labor-augmenting technology decreased between 1979 and 2007, while high-skilled technology increased. This is consistent with technology and competition from abroad replacing low-skilled workers and complementing high-skilled workers. Lastly, the model recovers a mean and standard deviation of ability somewhat able to replicate the share of prime-age men who chose the high-skilled market.

Table 2.3 shows the model matches the targeted moments quite well. I target the levels of tightness and wages, but for illustration purposes also show how well the model matches the percent gaps between the high- and low-skilled. The model slightly

overestimates high-skilled tightness in 2007, leading to a larger gap than what is observed in the data. The model also slightly overestimates the wage gap in 1979, however, it still hovers around zero meaning average wages in the late 1970s were similar between high- and low-skilled occupations. The model underestimates the large wage gap that emerged in the 2000s, yet it still produces over a twofold increase. Lastly, the model replicates the fact that in the 1970s there were fewer men in the high-skilled market than there are today. The model somewhat matches the college share in 1979, but over predicts the share in 2007.

Table 2.4 then compares the model's generated employment rates with the data, which are technically non-targeted moments. The model directly targets job finding and separation rates. In the model, steady state employment is determined by setting job finding and separation rates equal to each other. The model will match the data to the extent 1979 and 2007 are in fact steady states. The model captures both high- and low-skilled employment rates hovered around 90 percent in 1979 and the low-skilled employment rate fell to the low eighties by 2007. Overall, the model predicts the employment gap increased by 3.3 percentage points over this period, nearly matching the 3.4 percentage point rise we observe in the data.

Figure 2.5 illustrates results of counterfactual exercises. The vertical axis depicts how much the employment gap changed between 1979 to 2007, in percentage points. The red bar represents the data, with an employment gap increase of 3.4 percentage points as displayed in Table 2.4. The dark blue bar represents the model with all of its channels turned on. The subsequent light blue bars illustrate the change in the employment gap when each channel is turned on one at a time. In other words, if all but one parameter is fixed at its 1979 level and the remaining parameter evolves according to Table 2.2, what would happen to the employment rate gap?

Turning to the most leftward light blue bar, we see when value of leisure for

both the low- and high-skilled changes according to its calibrated value and all other channels are turned off, the employment gap increases by only 0.2 percentage points from 1979 to 2007. In other words, a relative change in lower skilled workers' value of leisure barely widened the employment gap.<sup>24</sup> The direction is consistent with increases in government spending on disability insurance over this period, which Barnichon and Figura (2015a) and the Council of Economic Advisors' 2016 Economic Report of the President document and propose as possible evidence for an increase in low-skilled workers' value of non-work activity. However, Appendix 2.16 reveals this result is not robust to alternative specifications. When alternative education cutoffs for defining a vacancy are used, the value of leisure channel may narrow the employment rate gap, while qualitatively all other results are robust. Therefore, I conclude a supply shift has not robustly altered employment inequality since the 1970s.

The SBTC and trade channel, on the other hand, robustly increased employment inequality over this period. If labor-augmenting technology for both the low- and high-skilled changes according to its calibrated value and all other channels are turned off, the employment gap increases by nearly 5 percentage points. In other words, an increase in the relative productivity of high-skilled labor increased demand for high-skilled labor, and can account for all (and more) of the observed rise in employment inequality. This result is consistent with Autor, Katz, and Krueger (1998) who find a demand-side explanation led to approximately a 3-4% annual increase in the wage gap from 1970 to 1996.

The second most rightward bar reveals if matching efficiency is the only channel turned on, the employment gap would be negative, meaning search frictions actually reduced employment inequality. In 1979, the high-skilled labor market was more efficient than the low-skilled labor market at matching job-seekers with job openings,  $\phi_{H,79} > \phi_{L,79}$ . However, in 2007, the low-skilled market was more efficient at this process than the

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<sup>24</sup>In Table 2.2, low-skilled value of leisure decreased in absolute terms, but decreased by less than high-skilled value of leisure.



high-skilled,  $\phi_{H,07} < \phi_{L,07}$ . One possible explanation is lower skilled workers have been relatively more mobile. Molloy, Smith, and Wozniak (2014) find interstate migration decreased for all education levels between the 1980s and 2000s, but the decrease was monotonically larger for the more educated. Another explanation is high-skilled, college jobs became more specialized over this period, such that high-skilled jobs-seekers have more difficulty finding good matches. Lastly, if job separation rates were fixed at their 1979 levels, there would be minimal employment inequality. Separations are exogenous in this setup and come directly from the data, however, possible explanations for the rise in low-skilled job separations include the decline of unions and a change in the composition of firms.

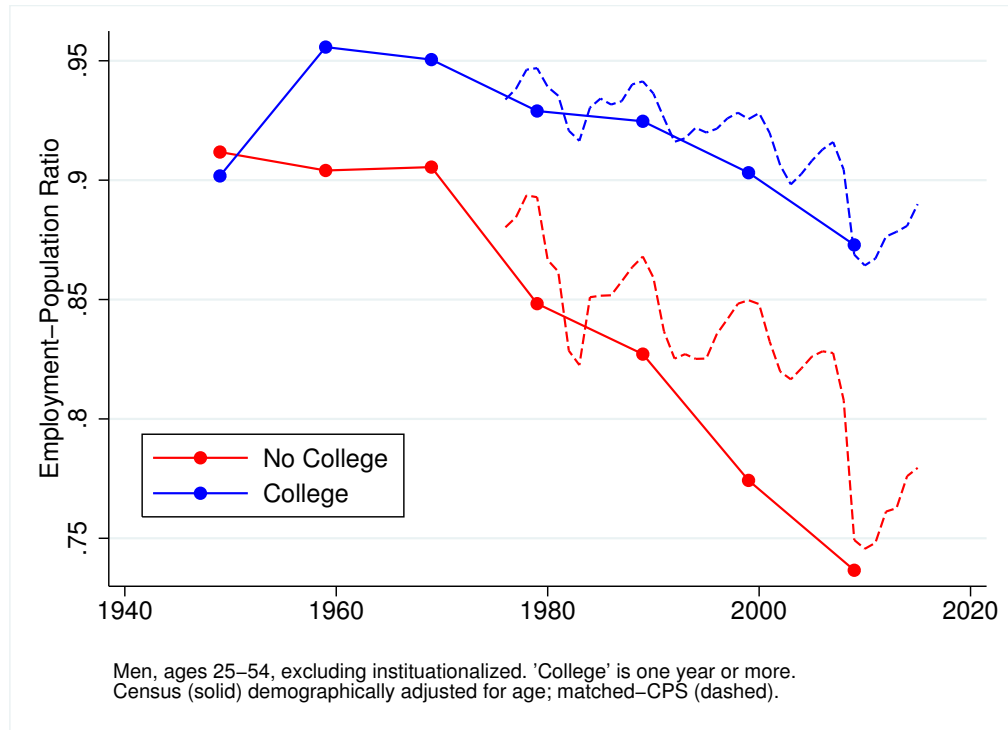
Diverging employment rates are driven by diverging outflows rather than inflows. Appendix 2.15 illustrates this by showing the spread in separation rates between high- and low-skilled workers increased over this period, while the spread in job finding rates remained constant. Job finding rates in this setup are a function of matching efficiency and market tightness, where the latter is a function of value of leisure and labor-augmenting technology. Figure 2.5 shows matching efficiency narrowed the employment rate gap, while the value of leisure, and SBTC/trade widened the gap. On net, search frictions offset the supply and demand shifts such that job finding rate did not contribute to rising employment inequality. Instead, all the bite came from separations.

## 2.7 Conclusion

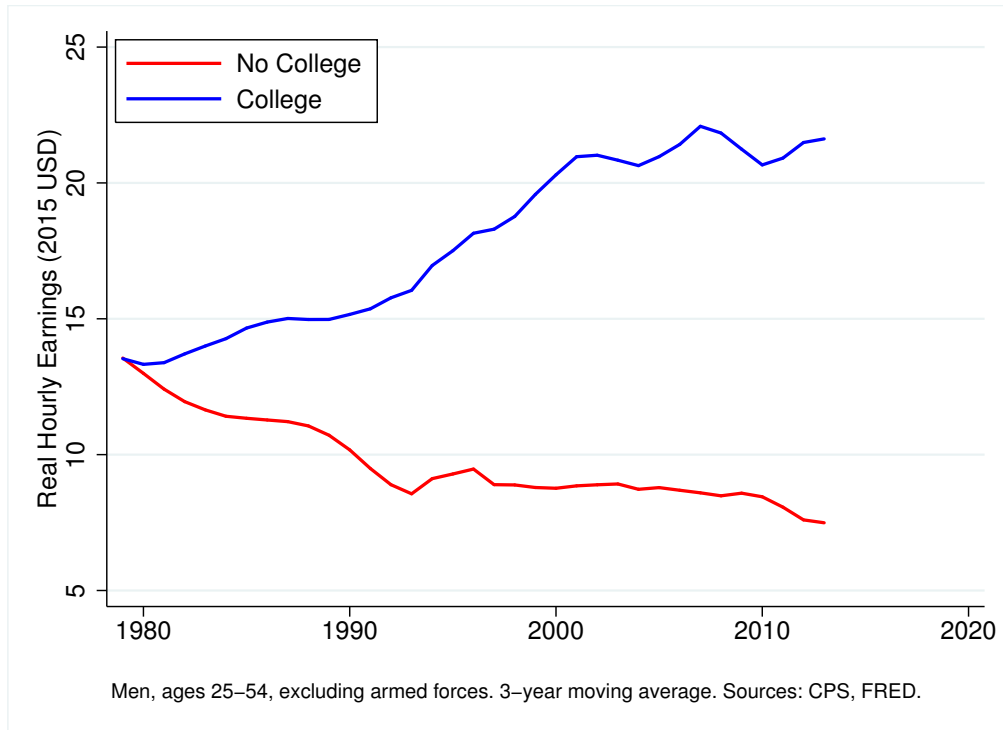
In this paper, I explore what mechanisms account for diverging employment rates. Employment rates between college and non-college men began to differ in the 1960s and have been diverging ever since. I calibrate an augmented DMP model to match two business cycle peaks, 1979 and 2007, and compare the recovered parameters.

This approach differs from previous work because I allow for labor market frictions, in addition to supply and demand shifts, to account for the widening employment rate gap. In particular, I examine the role of matching efficiency by targeting a novel empirical fact: the divergence of labor market tightness by skill. Because the spread in job finding rates between college and non-college workers remained constant over this period, but labor market tightness for higher skilled jobs increased, I find matching efficiency increased for lower skilled jobs and narrowed the employment rate gap. Nevertheless, an increase in low-skilled separations along with a rise in high-skilled productivity widened the employment rate gap. On net, this led to a three percentage point increase in the spread of college and non-college male employment rates between 1979 and 2007.

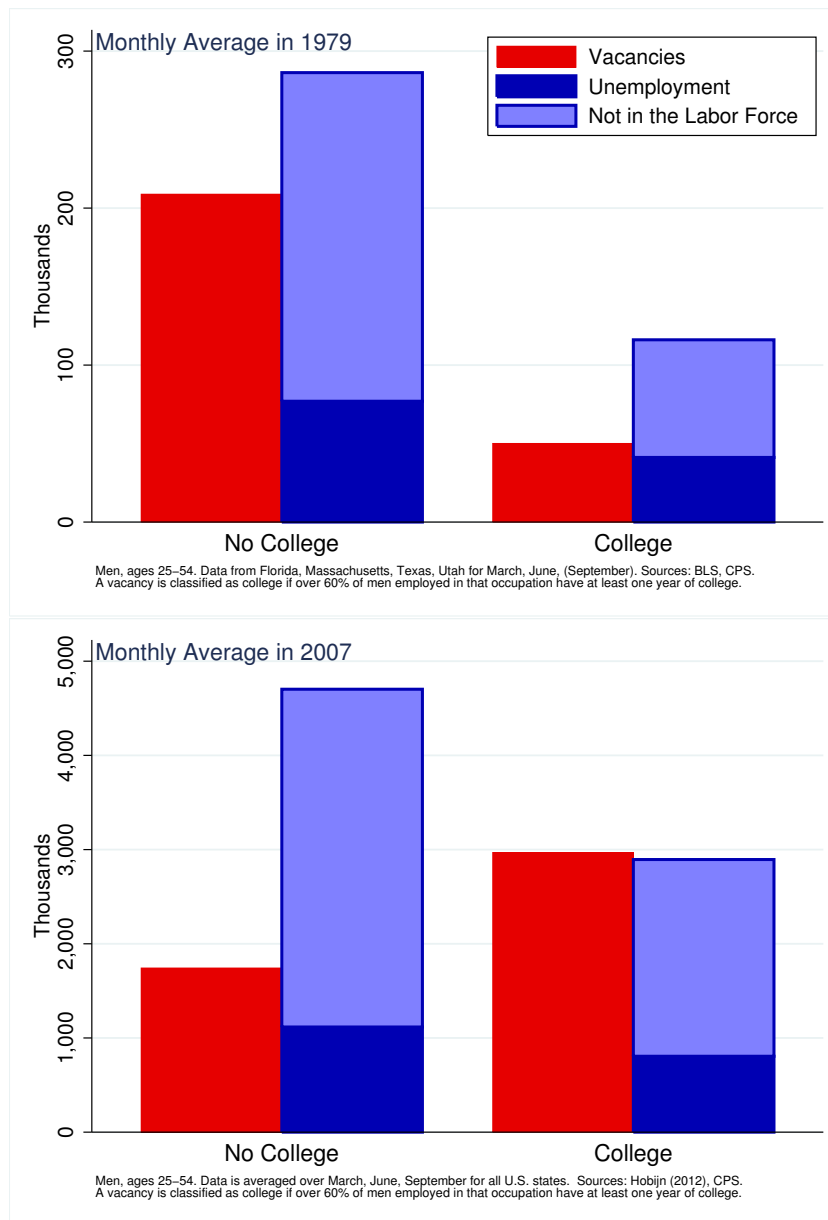
Chapter 2 is currently being prepared for submission for publication; Erin L. Wolcott. The dissertation author was the principal author on this paper.



**Figure 2.1:** Widening Employment Gap



**Figure 2.2:** Widening Wage Gap

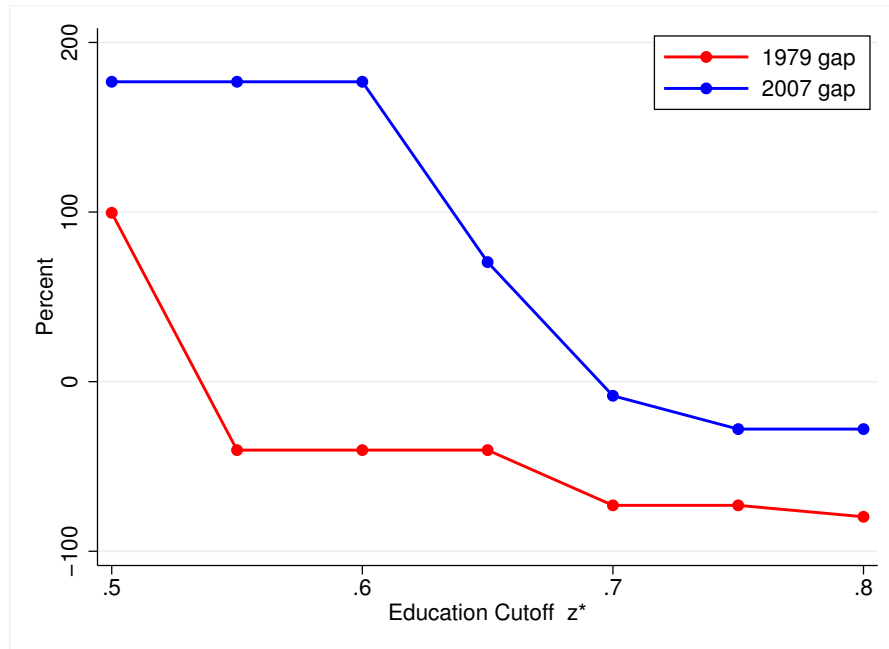


**Figure 2.3: Differential Market Tightness**

**Table 2.1:** Tightness Ratios

Measure	Year	Data Sources	$\theta_H$	$\theta_L$	Gap
Nonemployment	1979	BLS, CPS	0.44	0.73	<b>-40%</b>
Nonemployment	2007	Hobijn (2012), CPS	1.03	0.37	<b>177%</b>
Unemployment	1979	BLS, CPS	1.22	2.71	<b>-55%</b>
Unemployment	2007	Hobijn (2012), CPS	3.68	1.56	<b>136%</b>

Men, ages 25-54. Reported tightness is the monthly average over March, June, September in 1979 and March, April, May in 2007. Utah in 1979 is the exception; tightness is only averaged over March and June. Data from 1979 only includes Florida, Massachusetts, Texas, and Utah.



**Figure 2.4:** Tightness Gap by Educational Cutoff

**Table 2.2:** Parameter Estimates for 1979 and 2007 Steady States

Parameter	Explanation	Value	Source
$\beta$	discount factor	0.9967	monthly rate
$\alpha_{j,t}$	matching elasticity	0.62	Veracierto (2011)
$\pi_{j,t}$	bargaining weight	0.62	Hosios condition
$\kappa_{j,t}$	vacancy posting cost	0.5	share of 1979 offer wages
$\delta_{L,79}$	separation rate	0.0223	CPS
$\delta_{L,07}$	separation rate	0.0326	CPS
$\delta_{H,79}$	separation rate	0.0121	CPS
$\delta_{H,07}$	separation rate	0.0162	CPS
$\phi_{L,79}$	matching efficiency	0.1892	CPS job finding rate=0.1679
$\phi_{L,07}$	matching efficiency	0.2116	CPS job finding rate=0.1451
$\phi_{H,79}$	matching efficiency	0.2710	CPS job finding rate=0.1975
$\phi_{H,07}$	matching efficiency	0.1593	CPS job finding rate=0.1608
$b_{L,79}$	value of leisure	0.30	calibrated
$b_{L,07}$	value of leisure	0.26	calibrated
$b_{H,79}$	value of leisure	0.63	calibrated
$b_{H,07}$	value of leisure	0.57	calibrated
$A_{L,79}$	technology	1.05	calibrated
$A_{L,07}$	technology	0.69	calibrated
$A_{H,79}$	technology	0.66	calibrated
$A_{H,07}$	technology	1.11	calibrated
$\mu_x$	mean ability	0.35	calibrated
$\sigma_x$	standard deviation of ability	0.15	calibrated

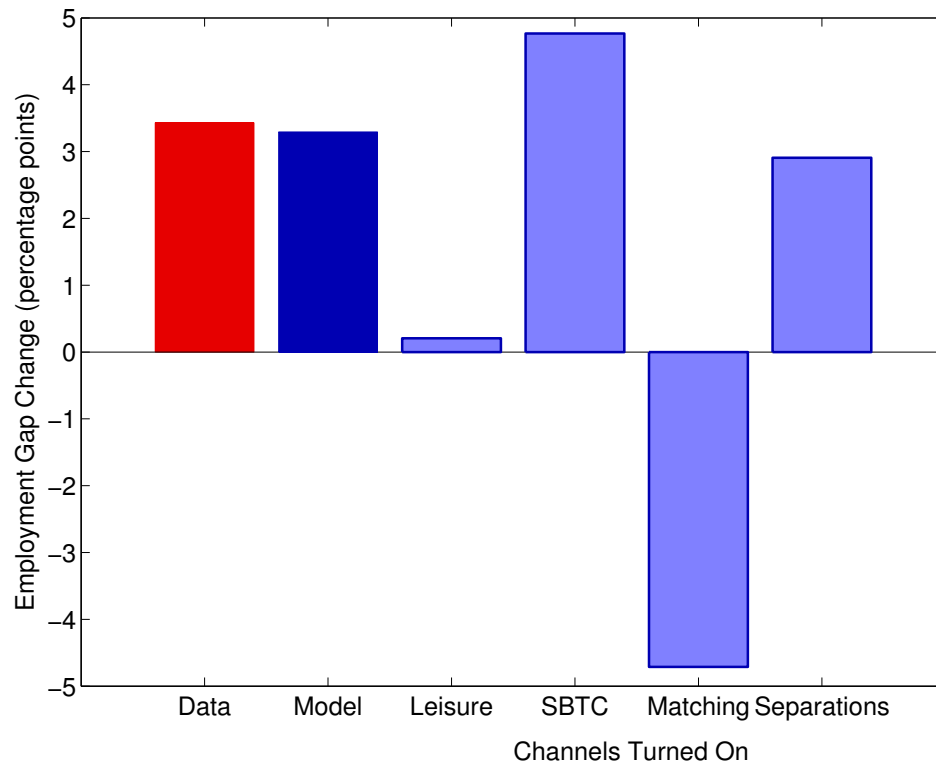


**Table 2.3:** Targeted Moments

Moment	Explanation	Year	Model	Data	Model Gap	Data Gap
$\theta_{L,79}$	L tightness	1979	0.73	0.73		
$\bar{\theta}_{H,79}$	H tightness	1979	0.43	0.44	-40%	-40%
$\theta_{L,07}$	L tightness	2007	0.37	0.37		
$\bar{\theta}_{H,07}$	H tightness	2007	1.05	1.03	184%	177%
$\omega_{L,79}$	L wages (normalized)	1979	0.99	1.00		
$\bar{\omega}_{H,79}$	H wages	1979	1.00	1.00	2%	0%
$\omega_{L,07}$	L wages	2007	0.64	0.63		
$\bar{\omega}_{H,07}$	H wages	2007	1.53	1.60	138%	154%
$\frac{100 \times (M - \xi)}{M}$	H share	1979	50%	43%		
$\frac{100 \times (M - \xi)}{M}$	H share	2007	90%	56%		

**Table 2.4:** Non-Targeted Moments

Moment	Explanation	Period	Model	Data	Model Gap	Data Gap
$e_{L,79}$	L employment rate	1979	88%	89%		
$\bar{e}_{H,79}$	H employment rate	1979	94%	95%	5.9 pp	5.4 pp
$e_{L,07}$	L employment rate	2007	82%	83%		
$\bar{e}_{H,07}$	H employment rate	2007	90%	92%	9.2 pp	8.8 pp
Difference					3.3 pp	3.4 pp



**Figure 2.5:** Counterfactuals

## 2.8 Appendix: Baseline Vacancy Categorization, $z^* = 0.6$

**BLS Pilot Vacancy Data**  
(2-digit 1977 SOC)

**Hobijn (2012) Vacancy Data**  
(2-digit 2000 SOC)

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### High-Skilled Occupations

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Executive, Administrative & Managerial  
Engineers & Architects  
Natural Scientists & Mathematicians  
Social Scientists, Social Workers, Religious Workers & Lawyers  
Teachers, Librarians & Counselors  
Health Diagnosing & Treating Practitioners  
RNs, Pharmacists, Dietitians, Therapists & Physicians Assistants  
Writers, Entertainers, Artists & Athletes  
Health Technologists & Technicians  
Marketing & Sales

Management  
Business and Financial Operations  
Computer & Mathematical Science  
Architecture and Engineering  
Life, Physical & Social Science  
Community and Social Services  
Legal  
Education, Training & Library  
Arts, Design, Entertainment, Sports & Media  
Healthcare Practitioners & Technical  
Healthcare Support  
Protective Service  
Personal Care & Service  
Sales & Related  
Office & Administrative Support  
Installation, Maintenance & Repair

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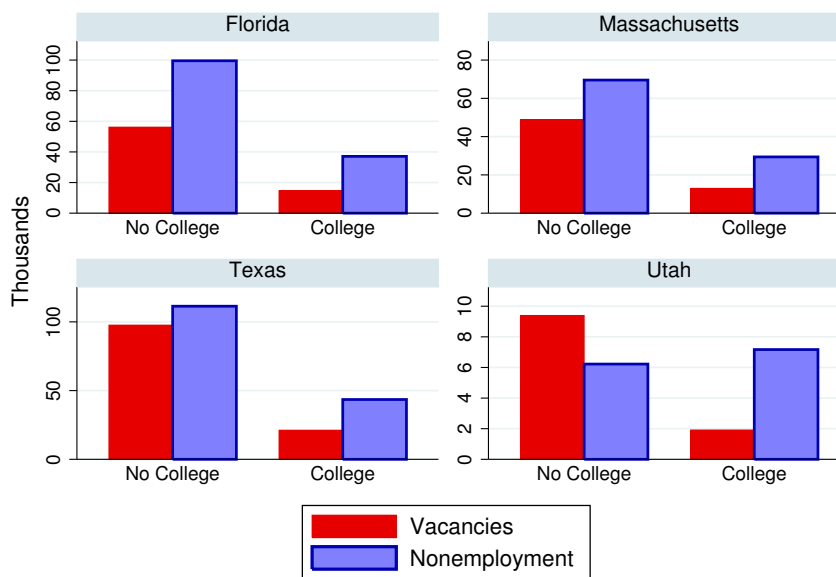
### Low-Skilled Occupations

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Clerical Occupations  
Construction & Extractive Occupations  
Agricultural, Forestry, Fishers & Hunters  
Transportation & Material Moving  
Construction & Extraction  
Production  
Transportation & Material Moving

Food Production & Serving Related  
Building & Grounds Cleaning & Maintenance  
Farming, Fishing, and Forestry  
Mechanics & Repairers  
Production Work Occupations  
Material Handlers, Equipment Cleaners & Laborers

## 2.9 Appendix: Tightness Gap by State in 1979



Men, ages 25-54. Data averaged over March, June, (September). Sources: BLS, CPS.

**Figure 2.6:** Tightness Gap by State in 1979

**Table 2.5:** Tightness Gap by State in 1979

### Tightness Gap

Florida	-30%
Massachusetts	-37%
Texas	-44%
Utah	-82%

## 2.10 Appendix: Tightness Gap by Year in the 2000s

**Table 2.6:** Tightness Gap by Year in the 2000s

<b>Hobijn (2012) and CPS Data</b>			
Year*	$\theta_H$	$\theta_L$	Percent Gap
2005	0.848	0.314	170
2006	0.898	0.395	128
2007	1.026	0.370	177
2008	0.805	0.266	203
2009	0.386	0.100	286
2010	0.466	0.127	268
2011	0.458	0.158	191
2012	0.579	0.204	184
2013	0.581	0.278	135

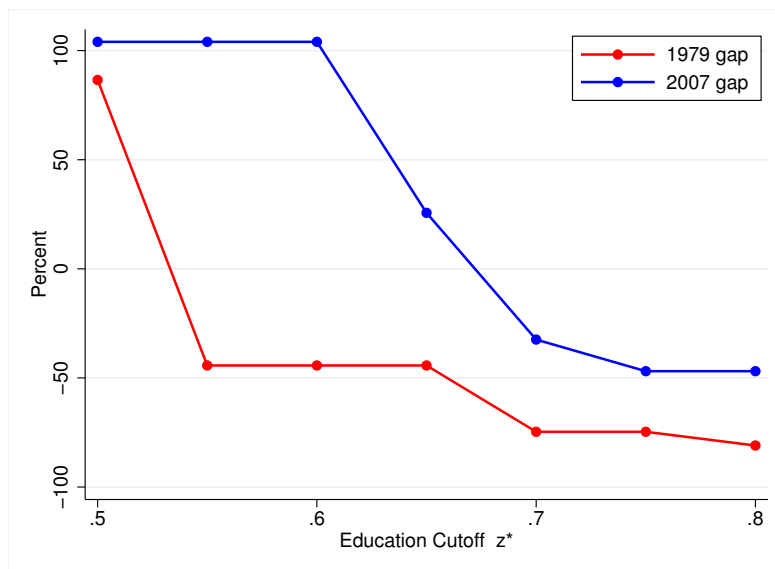
\*Tightness is averaged over 3 months in the second quarter of the reference year.

## 2.11 Appendix: Tightness with Alternative Denominator

This appendix calculates labor market tightness using the number of prime-age men and women who are unemployed in the denominator. This is in contrast to the unemployment measure in Table 2.1, which uses only prime-age men. If vacancy creation is differentially affected by female labor force participation, tightness ratios in Table 2.1 may bias matching efficiency. However, since the tightness gap including unemployed women is similar to the baseline, I can rule out this type of biases. Moreover, in using this alternative measure we see the high-skilled market is substantially tighter than the low-skilled market for various education cutoffs  $z^*$ , as is the case with the baseline measure in Figure 2.4.

**Table 2.7:** Tightness Ratios Including Women

Measure	Year	Data Sources	$\theta_H$	$\theta_L$	Percent Gap
Unemployment	1979	BLS, CPS	0.5891	1.0574	<b>-44.3</b>
Unemployment	2007	Hobijn (2012), CPS	1.7888	0.8768	<b>104</b>



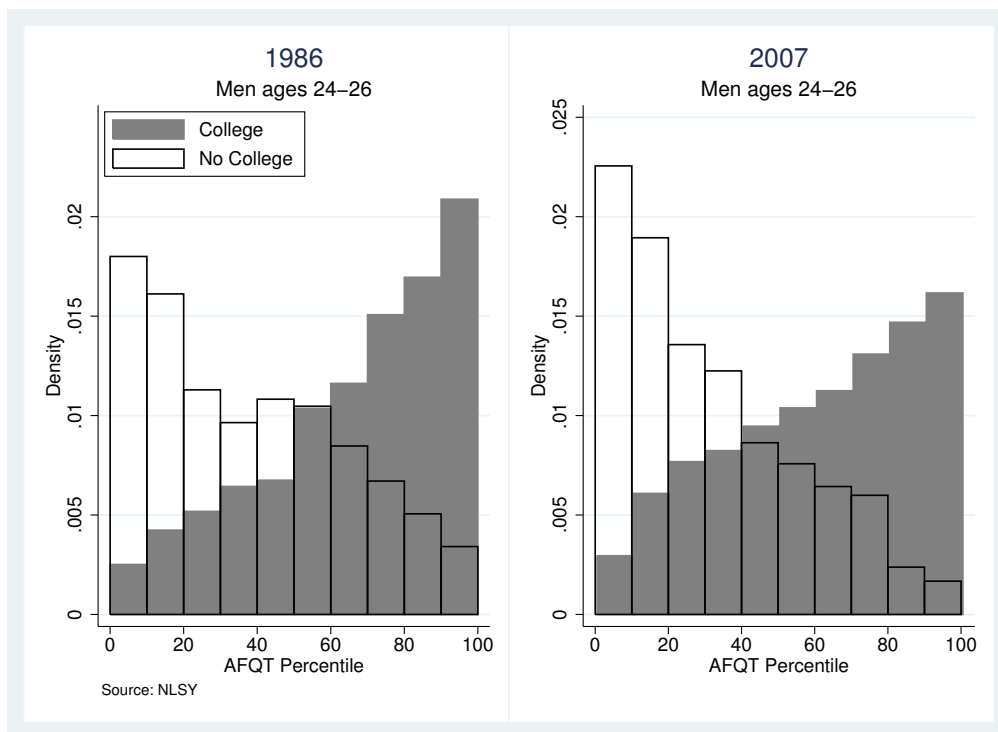
**Figure 2.7:** Percent Gap by Education Cutoff: Unemployment Measure Including Women

## 2.12 Appendix: Ability Composition

The structural framework in this paper adds three ingredients to the standard DMP model. Two of the three ingredients are heterogeneous ability and occupational choice. This appendix illustrates the composition of low- and high-skilled workers has changed over the last few decades. Workers searching for college and non-college jobs in the 2000s are of lower ability than workers in the 1980s. Such ability sorting likely has implications for labor market conditions across the two groups and therefore is an important feature for the model to match. Cunha, Karahan, and Soares (2011) and Carneiro and Lee (2011) make a similar point about the importance of ability sorting and relate it to the college premium.

Specifically, I document the ability composition of men who attended college and men who did not attend college has changed over time. This is not to say particular individuals moved across categories, but rather particular ability levels have historically moved across categories. The population with some college experience in the 1980s was made up of people with certain permanent characteristics and today it is made up of people with different permanent characteristics.

To illustrate this I use two cohorts of the National Longitudinal Survey of Youth (NLSY). Respondents from the 1979 cohort were ages 14 to 22 during the first year of the survey and respondents from the 1997 cohort were ages 12 to 16 during the first year of the survey. Within the first two years of each survey's inception both cohorts were administered the Ability Services Vocational Aptitude Battery (ASVAB). The ASVAB consists of a battery of 10 tests intended to measure developed abilities and



**Figure 2.8:** Compositional Change of College and Non-College

help predict future academic and occupational success in the military.<sup>25</sup> The NLSY reports a composite score derived from select sections of the battery used to approximate an unofficial Armed Forces Qualifications Test score (AFQT) for each youth. The AFQT includes the following four sections of the ASVAB: arithmetic reasoning, world knowledge, paragraph comprehension, and numerical operations.<sup>26</sup> Furthermore, the NLSY's AFQT-3 variable re-norms scores, controlling for age, so that scores from the 1979 and 1997 cohorts are comparable. Percentile of AFQT scores are reported on the horizontal axis of Figure 2.8.

The left panel of Figure 2.8 plots a subset of the 1979 cohort in 1986. The right panel plots a subset of the 1997 cohort in 2007. Years are chosen so age groups and places in the business cycle are comparable across panels. Turning to the gray bars, in 1986, men in the 90th percentile of the AFQT distribution (the most rightward gray bar) made up 21% of the college population, while in 2007 the 90th percentile made up only 16%. Moreover, men in the 60th percentile made up a larger share of the college population in 1986 than in 2007. Put differently, the college population consisted of lower-ability prime-age men in 2007.<sup>27</sup>

<sup>25</sup><http://official-asvab.com>

<sup>26</sup><https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/education/aptitude-achievement-intelligence-scores/page/0/0/#asvab>

<sup>27</sup>The two-sample Kolmogorov-Smirnov test rejects the null hypothesis at the 1% level that college respondents in both years come from the same AFQT distribution.



Turning to the clear bars, in 1987 the bottom 10% of the ability distribution (the most leftward clear bar) made up 18% of the non-college population, while in 2007 it made up 23%. Moreover, the bottom 40% made up a larger share of the non-college population in 2007 than in 1986. In other words, the non-college population consisted of lower-ability prime-age men in 2007.<sup>28</sup>

To summarize, the ability composition of the college and non-college labor market has changed.<sup>29</sup> In the model, workers endogenously choose whether to search for college or non-college jobs based on their underlying ability. The model is able to match the fact that median worker ability in both markets fell over the last few decades.

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<sup>28</sup>The two-sample Kolmogorov-Smirnov test rejects the null hypothesis at the 1% level that non-college respondents in 198 and 2008 come from the same AFQT distribution.

<sup>29</sup>Archibald, Feldman, and McHenry (2015) find despite college attendance rates rising, student quality at 4-year institutions has remained unchanged over the last few decades, while student quality at 2-year institutions has declined. The authors attribute unchanging student quality at 4-year institutions to better sorting; student characteristics other than grades and test scores, such as race and parents' education, have become less predictive. This trend is not the same at 2-year institutions and for students with at least one year of college or more (as shown above).

## 2.13 Appendix: Derivation of Equilibrium Wages

This derivation is adapted from that in Chapter 1 of Pissarides (2000). Time here is discrete rather than continuous.

Under Nash bargaining and free entry, if a worker matches he gets a share of the surplus  $\pi S_{jt}^c(x) = \pi(J_{jt}(x) + W_{jt}(x) - N_{jt}(x))$ . Since the worker gives up the value of nonemployment to receive the value of a match, this implies the difference must equal his share of the match surplus:

$$W_{jt}(x) - N_{jt}(x) = \pi(J_{jt}(x) + W_{jt}(x) - N_{jt}(x)). \quad (2.16)$$

To solve for the equilibrium wage, we will first solve for wages in terms of nonemployment. Substituting in equations (2.3) and (2.4) into equation (2.16) yields:

$$\omega_{jt}(x) = \pi y_{jt}(x) + (1 - \pi)(N_{jt}(x) - \beta \delta N_{jt+1}(x)) + \beta(1 - \delta) [\pi J_{jt+1}(x) - (1 - \pi)W_{jt+1}(x)]. \quad (2.17)$$

Rewriting equation (2.16) as  $-(1 - \pi)N_{jt+1}(x) = \pi J_{t+1}(x) - (1 - \pi)W_{jt+1}(x)$  and substituting it into equation (2.17) gives:

$$\omega_{jt}(x) = \pi y_{jt}(x) + (1 - \pi)(N_{jt}(x) - \beta N_{jt+1}(x)). \quad (2.18)$$

Next, I solve for the equilibrium path of nonemployment so I can plug it into equation (2.16) and solve for wages just as a function of parameters. Taking equation (2.6) and repeatedly substituting in (2.16) and the the equilibrium condition for jobs (2.3) results in:

$$N_{jt}(x) - \beta N_{jt+1}(x) = b_j + \frac{\pi \kappa f_{jt}(\theta)}{q_{jt}(\theta)} [1 + \pi + \pi^2 + \pi^3 + \dots]. \quad (2.19)$$

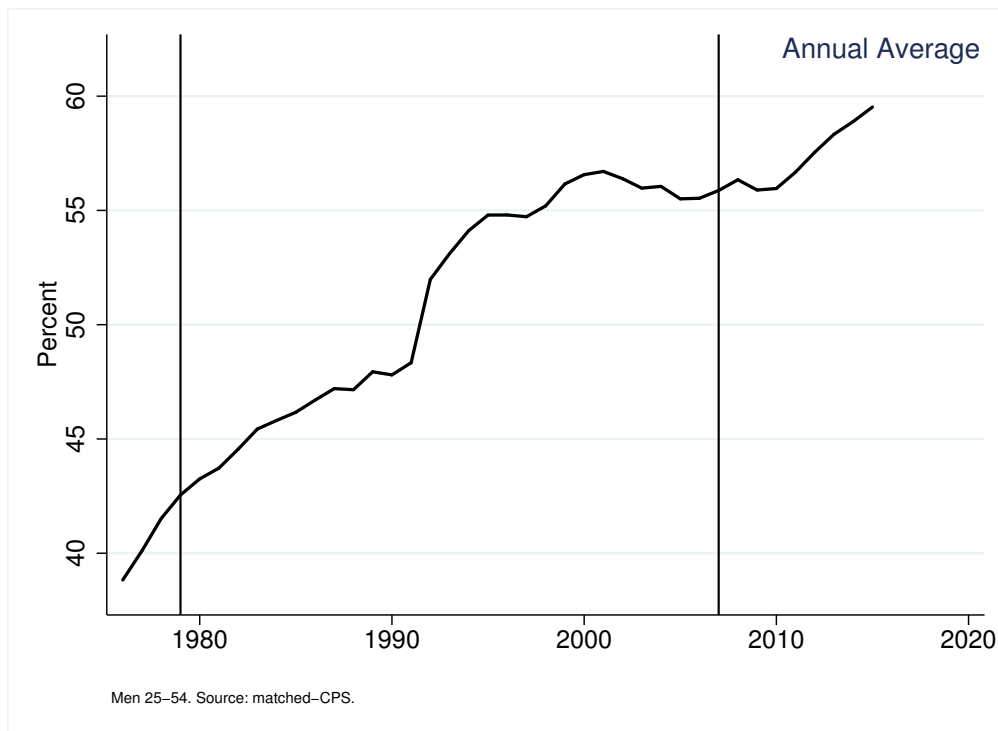
Inserting functional forms for the job finding and filling rates as well as the expression of the sum of an infinite geometric series yields:

$$N_{jt}(x) - \beta N_{jt+1}(x) = b_j + \left( \frac{\pi \kappa}{1 - \pi} \right) \theta. \quad (2.20)$$

An equation for the equilibrium wage results for combining equations (2.18) and (2.20)

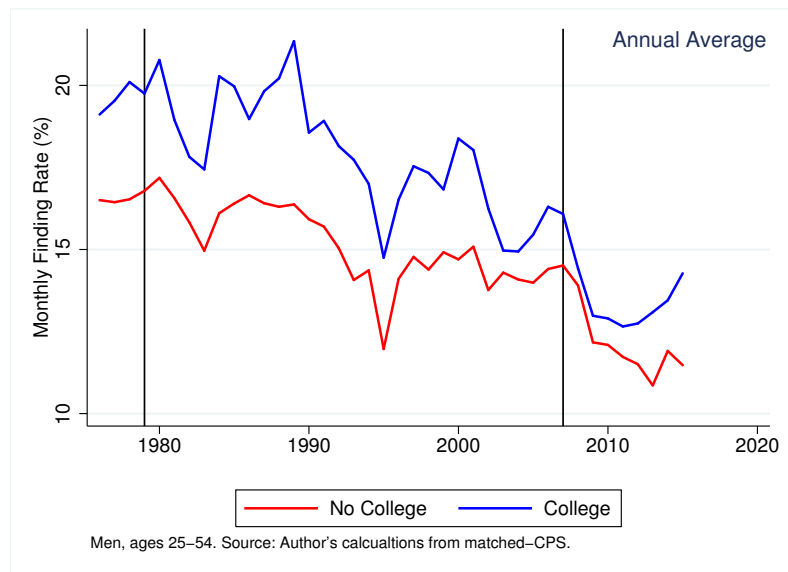
$$\omega_{jt} = (1 - \pi)b_j + \pi(y_{jt}(x) + \kappa\theta). \quad (2.21)$$

## 2.14 Appendix: Time Series of College Share

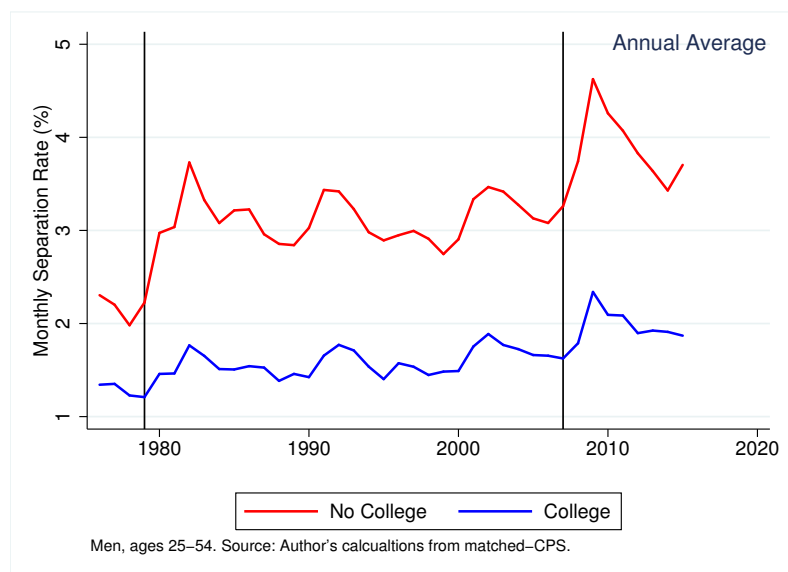


**Figure 2.9:** Share of Prime-age Men with at Least One Year of College

## 2.15 Appendix: Time Series of Worker Flows

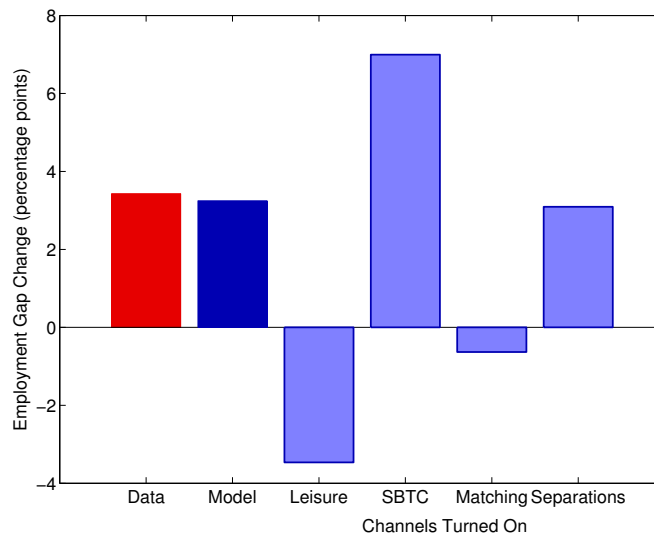


**Figure 2.10:** Job Finding Rates:  $U+NLF \rightarrow E$

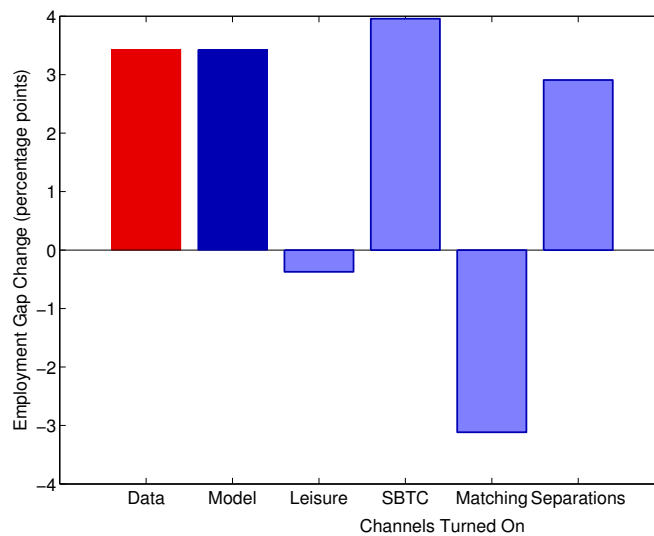


**Figure 2.11:** Separation Rates:  $E \rightarrow U+NLF$

## 2.16 Appendix: Counterfactuals with Alternative Education Cutoff $z^*$



**Figure 2.12:** Education Cutoff  $z^* = 0.5$

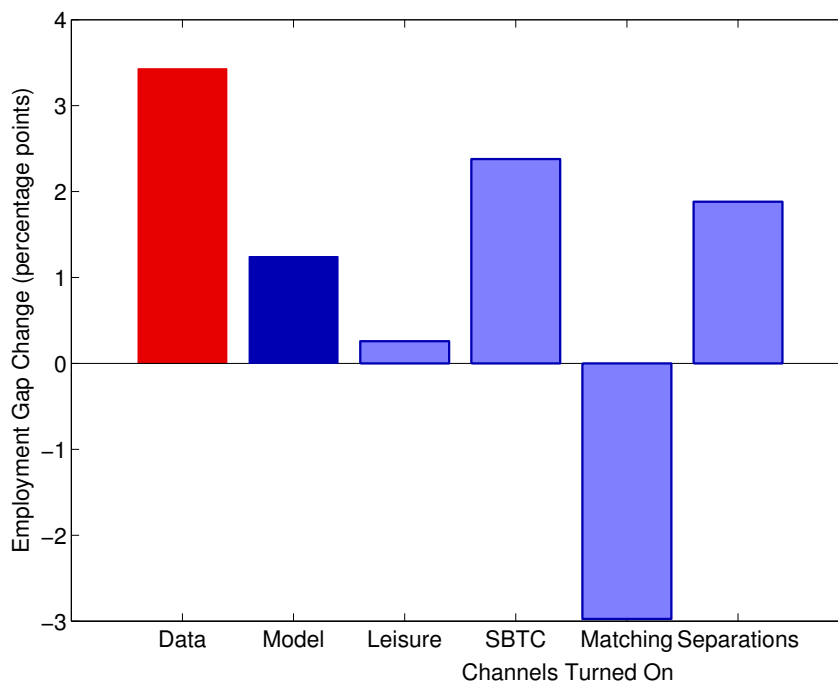


**Figure 2.13:** Education Cutoff  $z^* = 0.65$

## 2.17 Appendix: Counterfactuals with Alternative Matching Efficiency

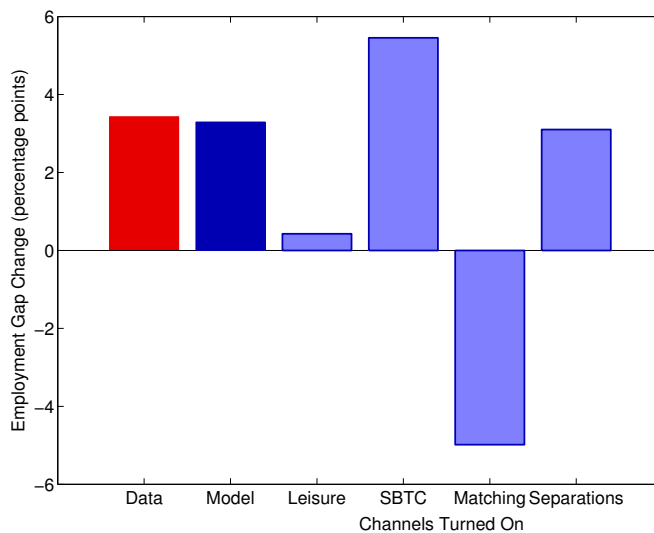
**Table 2.8:** Estimates of Matching Efficiency for Unemployed Men and Women

$\phi_{L,79}$	matching efficiency	0.2674	CPS job finding rate = 0.2732
$\phi_{L,07}$	matching efficiency	0.2952	CPS job finding rate = 0.2808
$\phi_{H,79}$	matching efficiency	0.3602	CPS job finding rate = 0.2946
$\phi_{H,07}$	matching efficiency	0.2214	CPS job finding rate = 0.2762

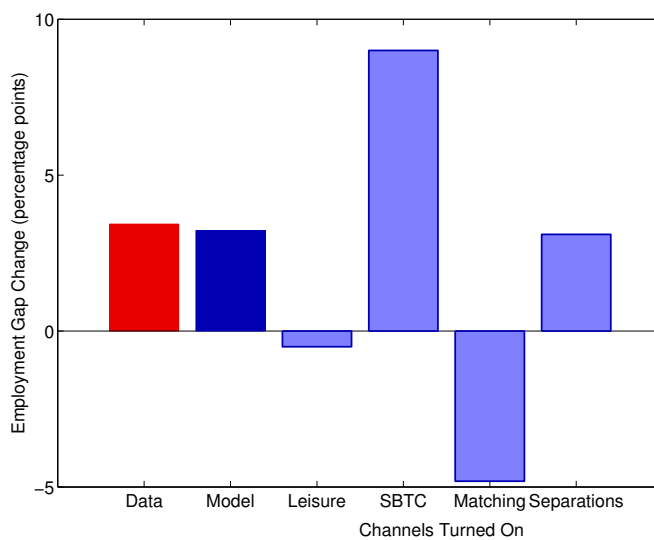


**Figure 2.14:** Counterfactuals with Matching Efficiency for Unemployed Men and Women

## 2.18 Appendix: Counterfactuals with Alternative Parameterization



**Figure 2.15:** Counterfactuals with Bargaining Power  $\pi_L = 0.52$  and  $\pi_H = 0.72$



**Figure 2.16:** Counterfactuals with Vacancy Posting Costs  $\kappa_L = 0.3$  and  $\kappa_H = 0.7$

# Chapter 3

## Occupational Mismatch and the Cyclicalities of New Hire Wages

### 3.1 Abstract

We study why wages of newly hired workers are more pro-cyclical than wages of workers who do not switch jobs. Possible explanations include: (1) the labor market is tighter during expansions so firms offer higher wages to attract new workers, and (2) newly hired workers are better matched during expansions; in recessions workers take whatever job they can get. We find the latter explanation to be the predominant reason. We construct a novel measure of occupational mismatch by combining task data from O\*NET with the Survey of Income and Program Participation (SIPP) and compare a new hire's current skill profile to his previous skill profile. Including our measure of occupational mismatch in standard wage regressions can account for most of the new hire wage cyclicalities previously documented in the literature. This has implications for monetary policy and search theory. If wages of new hires are depressed during recessions because of poor match quality, rather than less demand, policy-makers may overestimate



slack when interpreting wage data. Additionally, our results suggest accounting for occupational mismatch is crucial for understanding how wages of new hires vary over the cycle, which is a critical margin of adjustment in standard search models.

## 3.2 Introduction

Wages are pro-cyclical, meaning they increase in expansions and fall in recessions. Wages of workers who start a new job—which we refer to as new hires—are extra pro-cyclical, meaning wages of this group fluctuate even more with the business cycle relative to wages of workers who stay at the same job—which we refer to as job stayers.<sup>1</sup>

There are two explanations for why wages of new hires display excess cyclicity relative to wages of existing workers. The first, more traditional explanation regards labor demand. In expansions the labor market is tight so firms may have to offer higher wages to attract new workers. Existing workers have contracts that are infrequently renegotiated, hence why new worker wages respond more. The second explanation regards worker composition. In recessions workers may take whatever job they can get, reducing match quality and ultimately wages. Policy-makers rely heavily on wage data when assessing the economic environment so is important to understand what drives wage cyclicity. For example, policy-makers often attribute slow or nonexistent wage growth during recessions to suppressed labor demand, when in fact, wages may be low because of poor match quality.

Pissarides (2009) argues the cyclicity of new hire wages contradicts the wage rigidity hypothesis. Historically, labor-search models have been unsuccessful at replicating the unemployment volatility we observe in the data. This is known as the unemployment-volatility puzzle (Shimer (2005)). Hall (2005), Shimer (2005), and

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<sup>1</sup>See Bils (1985) and Gertler, Huckfeldt, and Trigari (2016).

Kudlyak (2014), among others, show including wage rigidity in search models increases the volatility of unemployment and improves their fit. Pissarides (2009) argues that because wages of new hires are flexible, wage rigidity is not an empirically grounded mechanism. Recently Gertler, Huckfeldt, and Trigari (2016) show wages of new hires are flexible precisely because of workers coming directly from other jobs, i.e. employment-to-employment (EE) transitions, not because of workers coming from nonemployment, i.e. nonemployment-to-employment (NE) transitions. In order for wage rigidity to increase unemployment volatility in search models, it must work through NE transitions. The fact that Gertler, Huckfeldt, and Trigari (2016) find NE wages are acyclical, instead of pro-cyclical, suggests wage rigidity is still a viable mechanism to resolve the unemployment-volatility puzzle. Gertler, Huckfeldt, and Trigari (2016) go on to speculate the reason wages of new hires making EE transitions are pro-cyclical is a composition story, because if it was a demand story, we would expect to see the price (wage) of underutilized resources (the unemployed) respond.

The contribution of this paper is to evaluate whether match quality can account for the wage cyclicalities of newly hired workers, particularly those coming directly from other jobs (i.e. EE new hires). By combining task data from O\*NET with the Survey of Income and Program Participation (SIPP), we construct a measure of occupational mismatch and find it can account for most of new hire wage cyclicalities. Including our measure in standard wage regressions eliminates the predictive power of new hires making EE transitions during a sluggish economy. In other words, wages of new hires are pro-cyclical because workers moving from one job to another are poorly matched during recessions. This suggests policy-makers should pay attention to compositional effects as a source of wage fluctuations. Additionally, because our measure cannot explain why new hires making NE transitions are a-cyclical, we argue, like Gertler, Huckfeldt, and Trigari (2016), rigid wages for EN workers is a fair assumption in search theory.

The paper is organized as follows: Section 3.3 describes the dataset; Section 3.4 constructs our measure of occupational mismatch; Section 3.5 presents the empirical framework; Section 3.6 concludes.

## 3.3 Data

### 3.3.1 O\*NET Data

To create a measure of individual skill mismatch for a dataset containing repeated cross sections, we merge data on skills (or tasks) from the U.S. Department of Labor's O\*NET 4.0 database with the Survey of Income and Program Participation (SIPP). For each occupation, O\*NET assigns ratings to a set of skills. Specifically, for each 8-digit 2002 Standard Occupation Classification (SOC) code, O\*NET rates 35 skills. Examples of these skills include reading comprehension, writing, critical thinking, coordination, etc. There are two rating measures. One measure rates the "importance" of each skill to a specific occupation on a scale of 1 to 5 and another measure rates the "level" used of each skill on a scale of 0 to 7. Following Blinder et al. (2009) and Wiczer (2015), we combine both the "importance" and "level" measures by a Cobb-Douglas with elasticity 0.5. We convert 8-digit SOC codes to 6-digit occupation codes, taking the simple average, in order to merge this data with the SIPP. We then use a crosswalk published by the National Crosswalk Center translating 6-digit 2002 SOC to 3-digit 2002 Census codes.<sup>2</sup> We merge this with the 2004 and 2008 SIPP panels. For the 1996 and 2001 panels of the SIPP, occupations are classified according to 1990 Census codes. Using a crosswalk published by King et al. (2015) we convert 1990 Census codes to 2002 Census codes,

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<sup>2</sup><https://www.xwalkcenter.org/index.php/classifications/crosswalks>

which we then merge with O\*NET, as we did for the later SIPP panels.<sup>3 4</sup>

### 3.3.2 Survey of Income and Program Participation (SIPP)

The SIPP is a repeated cross section with panels from 1996-2000, 2001-2003, 2004-2007, and 2008-2012. Each panel starts with a new set of nationally representative respondents and interviews them every four months for the four years. The survey is retrospective and asks about events for each of the previous four months. Following Gertler, Huckfeldt, and Trigari (2016) we only use data from the survey month to reduce recall bias and seam effects. Thus, each period  $t$  represents four months. We restrict attention to men ages 20-60 and drop observations if respondents are not employed at the time of the survey's inception. We also exclude respondents when they report working two jobs because it is difficult to identify which is the primary job.

## 3.4 Measures of Occupational Mismatch

We construct several measures of occupational mismatch. The first measure computes the Euclidian distance between the skill profile a respondent uses at his current occupation and the skill profile used at a previous occupation. A respondent's previous skill profile likely contains information about the skills in which he has accumulated human capital, which is a useful base to compare current skills. There are a variety of ways to measure a respondent's previous skill profile in the SIPP. In this chapter we restrict attention to the tasks a respondent used when he first entered the survey. Future work will examine a respondent's occupational history, weighting each observed occupation by the length of the employment spell. It is important to note that previously

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<sup>3</sup>King et al. (2015) technically publish a cross walk between 1990 and 2000 Census codes; however, 2000 and 2002 Census codes are the same except the latter has an extra zero.

<sup>4</sup>Auctioneers, elevator operators, and motor transportation are excluded because ratings for these occupations do not exist in O\*NET.

used skills are not perfect measures of innate or learned skills because the previous occupation may have been a poor match. We will see in Section 3.5 that interacting our measure of mismatch with the business cycle helps us distinguish skill upgrades from skill downgrades.

**Euclidian Distance Measure with 35 Skills:**

$$Mismatch_{it} = \left[ \sum_{s=1}^{35} (Current_{its} - Previous_{is})^2 \right]^{1/2}, \quad (3.1)$$

where an individual  $i$ 's current use of skill  $s$  at time  $t$  is captured by  $Current_{its}$  and individual  $i$ 's previous use of skill  $s$  is captured by  $Previous_{is}$ .

There are numerous ways to measure distance. Moreover, there are numerous ways to weight the 35 skills; equation (3.1) equally weights each skill. We propose an alternative measure, which (i) uses the L1 norm instead of Euclidian distance and (ii) uses principal component analysis to construct weights, following Guvenen et al. (2015). We restrict attention to the first three principal components since they explain 80% of the total variation in our sample. Table 3.1 presents eigenvectors of these principal components. Even though this alternative measure differs from the baseline in multiple ways, results in Section 3.5 are robust.

**L1 Norm Measure with 3 Principal Components:**

$$Mismatch_{it}^{PC} = \sum_{p=1}^3 \left\{ \vec{w}_p' \times \left| Current_{it}^{\vec{}} - Previous_i^{\vec{}} \right| \right\}. \quad (3.2)$$

Here we rewrite variables  $Current_{it}^{\vec{}}$  and  $Previous_i^{\vec{}}$  as 35-element vectors, where each element represents a skill. Weights are contained in the 35-element vector  $\vec{w}_p$ . These are factor loadings of the  $p$ -th principal component.

One limitation of the measures defined in equations (3.1) and (3.2) is they convo-

lute whether workers are climbing up or down the skill ladder. For instance, a worker who switches to an occupation requiring a higher level of reading comprehension is indistinguishable from a worker who switches to an occupation requiring a lower level of reading comprehension. To separate skill upgrades from skill downgrades we study the three principal components separately. Table 3.1 lists eigenvectors of the three components, in descending order by the first component. "Complex Problem Solving," "Systems Analysis" and "Critical Thinking" (all analytic tasks) load heavily on the first component. "Troubleshooting," "Quality Control Analysis," and "Equipment Selection" (a mixture of analytic and routine tasks) load heavily on the second component. Lastly, "Management of Personnel Resources," "Equipment Maintenance," and "Time Management" (service-oriented or routine tasks) load heavily on the third component. I will refer to the first component as high-skill, the second as mid-skill, and the third as low-skill.

Unlike equations (3.1) and (3.2), the following directional measures for each principal component  $p$  can be negative. If an individual uses less of a particular skill-type (high, mid, or low) than he did in a previous occupation, this will show up in the directional measure as negative, i.e. down-skilling. For completeness, we also compute non-directional measures for each of the three principal components to examine if a particular skill type (high, mid, or low) drives our results.

**Directional Individual Component Measures:**

$$Directional_{it}^{PC} = \vec{w}_p' \times (Current_{it} - Previous_i),$$

where  $p \in \{1, 2, 3\}$  (3.3)

### Non-Directional Individual Component Measures:

$$NonDirectional_{itp}^{PC} = \vec{w}_p' \times \left| Current_{it} - Previous_i \right|,$$

(3.4)

where  $p \in \{1, 2, 3\}$

## 3.5 Empirical Framework

### 3.5.1 Baseline

Following Bilal (1985) and Gertler, Huckfeldt, and Trigari (2016), we begin with a simple regression studying how wages respond to a variety of conditions. In particular, we study how the log wage of individual  $i$  in 4-month interval  $t$  responds to whether that individual was hired at a new job  $\mathbb{1}\{NewHire_{it}\}$  and the health of the economy, as represented by the aggregate prime-age male unemployment rate  $U_t$ . The wage variable is the reported hourly wage for respondents who are hourly workers and an imputed wage for non-hourly workers, deflated by the PCE. The imputation uses a regression relating monthly earnings, hourly wage, hours worked per week, and weeks worked per month. We trim the top and bottom one percent of real wages. For the new hire variable we do not count men returning to the same job after a period of nonemployment as new hires. The regression includes an interaction term, and a set of characteristics on education, quadratic job tenure, marital status, and year fixed effects. Individual fixed effects are captured by  $x_i$  and the error term by  $\epsilon_{it}$ .

$$\begin{aligned} \ln Wage_{it} = & \alpha_0 + \alpha_1 \mathbb{1}\{NewHire_{it}\} \times U_t \\ & + \alpha_2 \mathbb{1}\{NewHire_{it}\} + \alpha_3 U_t \\ & + \alpha_4 Characteristics_{it} + x_i + \epsilon_{it} \end{aligned} \tag{3.5}$$

Table 3.2, column (1) displays results of estimating equation (3.5). The coefficient  $\alpha_1$  (the main coefficient of interest) represents how much extra wages change in response to both a worker being a new hire and the labor market having slack. As in the literature, we find this coefficient is negative and significant—in recessions, workers who start a new job earn lower wages than workers who stay in the same job. In other words, wages of new hires display excess cyclical relative to wages of existing workers. The coefficient  $\alpha_2$  represents how much extra wages change in response to both a worker being a new hire and the labor market being tighter. Table 3.2 reveals this coefficient is positive—in a well-functioning economy, workers who start a new job earn higher wages than those who stay in the same job (this finding is consistent with Bils (1985)). The coefficient  $\alpha_3$  represents how much wages of continuing workers change when the aggregate unemployment rate increases. As in the literature this coefficient is negative and significant; a one percentage point increase in the unemployment rate decreases wages of job stayers by 0.3 percent. Overall, we are able to replicate the signs on coefficients found in the literature. Next, we include a measure of occupational mismatch to study if match quality can explain why wages of new hires behave this way.

### 3.5.2 Including Occupational Mismatch

Table 3.2, column (2) displays results when we include occupational mismatch in equation (3.5). Mismatch variables throughout this paper are scaled by their within-individual standard deviation. We find the coefficient on mismatch to be positive and significant. A one standard deviation increase in task “distance” from an individual’s previous occupation is associated with a 0.15 percent wage increase. This is a bit surprising, however, when we interact mismatch with an dummy for new hire and the unemployment rate, as displayed in column (3) of Table 3.2, the story becomes clearer.

In column (3) of Table 3.2 we find the coefficient on the interaction between



new hire and the unemployment rate is halved in magnitude and no longer significant. In other words, by including our measure of match quality, new hire wages are no longer convincingly pro-cyclical. Moreover, mismatch of job stayers now predicts even larger wage gains, while mismatch of new hires predicts wage declines. In other words, workers who change skill sets in a healthy economy generally climb up the job ladder and experience wage gains, while workers who change skill sets in a sluggish economy make lateral or down-skilling occupational transitions and experience wage declines. Failing to distinguishing between transition in a healthy and unhealthy economy convolutes skill upgrading and downgrading and in aggregate (column (2)) fails to account for cyclicity of new hires like column (3) does. This finding is consistent with the model Moscarini (2001) writes down, where in a tight labor market workers with comparative advantages are the ones who switch jobs, while in a depressed labor market labor reallocations are noisier. Table 3.3 displays results using the three principal component measure of mismatch instead of the 35 skill Euclidean distance measure. Results are robust: using this alternative measure and its interactions reduces the cyclicity of new hire wages.

A natural question to ask is whether a single component, or skill changes in a certain direction, drive these results. For instance, does the principal component measure of mismatch, which treats all three components equally and treats skill upgrades and downgrades as one in the same, convolute multiple effects? To test this, we use the directional and non-directional measures defined in equations (3.3) and (3.4). The directional first principal component measure, is best described as skill upgrading. It captures the difference between high-skill tasks used today and high-skill tasks used previously. Table 3.4, column (1a) displays a subset of results from estimating equation (3.3) with the directional measure and all its interactions. The first row reveals the directional first principal component measure cannot account for new hire wage cyclicity. The coefficient on new hire interacted with unemployment is significant and almost as large,

in absolute value, as regressions excluding all mismatch variables. Column (1b) displays results from using the non-directional first principal component measure. The coefficient in the first row is also negative, but less significant and smaller in absolute value.

Columns (2a) and (2b) display results for the directional and non-directional measures of the *second* principal component, respectively. Columns (3a) and (3b) display results for the directional and non-directional measures of the *third* principal component, respectively. The first row of the (a) columns illustrate none of the directional measures can account for new hire wage cyclicality. The first row of the (b) columns illustrate non-directional measures of each principal component can account for some of the cyclicality. Generally, coefficients on the interaction between new hire and unemployment in the (b) columns are smaller and less significant, particularly for the low-skill (third) component. This implies one directional skill changes cannot explain the cyclicality, but dispersion in both up-skilling and down-skilling, particularly across low-skill tasks can. In other words, this is a story about occupational mismatch and the effects of skill transferability from one occupation to the next, regardless of whether the switch was a skill upgrade or downgrade.

The next section replicates the Gertler, Huckfeldt, and Trigari (2016) result that new hires are extra pro-cyclical because of workers transitioning from other jobs, as opposed to works transitioning from nonemployment. Gertler, Huckfeldt, and Trigari (2016) speculate this is due to worker composition. We test their hypothesis by including our measure of mismatch in the estimating equations.

### **3.5.3 Extended Empirical Framework**

In the previous section we find, like the literature, wages of new hires are pro-cyclical. In this section, we estimate the extended model in Gertler, Huckfeldt, and Trigari (2016) to study if this cyclicality is a function of a worker's previous employment status.

Specifically, we estimate the following equation, where *NewHireEE* is an indicator for whether an individual is newly hired and coming from another job and *NewHireNE* is an indicator for whether an individual is newly hired and coming from nonemployment.

$$\begin{aligned}
 \ln Wage_{it} = & \beta_0 + \beta_1 \mathbb{1}\{NewHireEE_{it}\} + \beta_2 \mathbb{1}\{NewHireNE_{it}\} + \beta_3 U_t \\
 & + \beta_4 \mathbb{1}\{NewHireEE_{it}\} \times U_t \\
 & + \beta_5 \mathbb{1}\{NewHireNE_{it}\} \times U_t \\
 & + \beta_6 OtherInteractions_{it} \\
 & + \beta_7 Characteristics_{it} + x_i + \varepsilon_{it}
 \end{aligned} \tag{3.6}$$

The coefficient  $\beta_1$  represents how average wages respond to a worker being both newly hired and making an employment-to-employment transition. As in the literature, this coefficient (Table 3.5, column (1), first row) is significant and as large as  $\alpha_1$  in Table 3.2. The coefficient  $\beta_2$  (Table 3.5, column (1), second row) is negative, but half the size of  $\beta_1$  and insignificant. In other words, wage cyclicality of new hires is mainly coming from EE transitions, not NE transitions.

Column (2) in Table 3.5 includes the mismatch measure, which is by itself is positive and significant. Column (3) interacts mismatch with new hire and the unemployment rate. Now, the coefficient on the interaction between new hire and unemployment for *both* EE and NE transitions is insignificant and small. In other words, our measure of mismatch can explain most of the new hire wage cyclicality found in the literature coming from EE. Table 3.6 displays results using the three principal component measure of mismatch instead of the 35 skill Euclidean distance measure. Results are robust: using this alternative measure reduces, and potentially eliminates, the wage cyclicality of new hires making EE transitions and does not affect the a-cyclicality of new hires making NE transitions.

### **3.6 Conclusion**

This paper examines why wages of newly hired workers display excess cyclical relative to wages of existing workers. We find occupational mismatch accounts for most of this cyclical. The distance between the skill profile a worker uses at his new job and the skill profile he used at a previous job strongly predicts wage cyclical. In fact, by including this variable in *Bils (1985)* and *Gertler, Huckfeldt, and Trigari (2016)*-type regressions, we can account for why wages of new hires decline in a sluggish economy. Moreover, through a series of alternative specifications, we rule out the possibility that the direction of skill change (up-skilling or down-skilling) drives our result. To conclude, we find wages of newly hired workers fall in recessions because these workers take jobs requiring different tasks than what they have accumulated human capital in. Lower match quality is the predominate reason why wages of these workers, particularly those coming from other jobs, co-move with the business cycle.

Chapter 3 is currently being prepared for submission for publication; Erin L. Wolcott and José Mustre-del-Río. The dissertation author was the principal author on this paper. The views expressed in Chapter 3 are those of the authors and should not be attributed to the Federal Reserve Bank of Kansas City or the Federal Reserve System.

**Table 3.1:** Principal Components Eigenvectors)

	Comp 1 High-skill	Comp 2 Mid-skill	Comp 3 Low-skill	Unexplained
Complex Problem Solving	0.223	0.0508	-0.0652	0.05372
Systems Evaluation	0.2179	0.0485	0.083	0.09274
Systems Analysis	0.217	0.057	0.081	0.09377
Active Learning	0.2166	0.0647	-0.1233	0.07523
Critical Thinking	0.2161	0.0541	-0.056	0.1088
Judgment and Decision Making	0.2143	0.0331	0.0442	0.1393
Reading Comprehension	0.2108	0.0157	-0.163	0.1331
Monitoring	0.2098	0.0311	0.0256	0.1769
Speaking	0.2089	-0.086	-0.0507	0.1323
Writing	0.2073	-0.05	-0.136	0.1561
Time Management	0.2011	-0.0088	0.2774	0.1267
Learning Strategies	0.2005	0.035	-0.0352	0.2448
Coordination	0.1991	-0.0022	0.2424	0.1713
Active Listening	0.1987	-0.097	-0.1193	0.1747
Negotiation	0.197	-0.0791	0.1941	0.1728
Persuasion	0.1958	-0.0858	0.059	0.2285
Management of Personnel Resources	0.195	0.0114	0.2935	0.156
Instructing	0.1916	0.0211	0.024	0.3167
Management of Financial Resources	0.1845	-0.0639	0.2351	0.2495
Management of Material Resources	0.1812	0.0799	0.2587	0.2354
Social Perceptiveness	0.1795	-0.1478	0.0968	0.2217
Operations Analysis	0.1783	0.1631	-0.1126	0.1878
Mathematics	0.1658	0.078	-0.2109	0.3728
Programming	0.1236	0.1406	-0.3848	0.3259
Service Orientation	0.1025	-0.1586	-0.0095	0.6131
Science	0.0901	0.2506	-0.2288	0.2843
Technology Design	0.0621	0.2882	-0.1977	0.2296
Quality Control Analysis	0.0614	0.3174	-0.0965	0.1444
Equipment Selection	0.0307	0.3125	-0.0034	0.2351
Troubleshooting	-0.001	0.3243	0.0365	0.1931
Installation	-0.0343	0.3066	0.0542	0.2538
Operation Monitoring	-0.048	0.2971	0.0856	0.2698
Operation and Control	-0.0775	0.2569	0.1774	0.3328
Repairing	-0.0971	0.2611	0.2641	0.1907
Equipment Maintenance	-0.0988	0.2679	0.2901	0.1336

**Table 3.2:** Baseline Model: Euclidean Distance Measure

VARIABLES	(1) lnWage	(2) lnWage	(3) lnWage
NewHire*U	-0.00210*** (0.000622)	-0.00222*** (0.000623)	-0.00123 (0.000950)
NewHire	0.00677* (0.00373)	0.00662* (0.00373)	0.0111* (0.00608)
U	-0.00322*** (0.000419)	-0.00294*** (0.000429)	-0.00112** (0.000495)
Mismatch		0.00151** (0.000654)	0.00873*** (0.00117)
NewHire*Mismatch			-0.00356** (0.00171)
Mismatch*U			-0.00114*** (0.000200)
NewHire*Mismatch*U			9.05e-05 (0.000273)
Constant	2.660*** (0.0241)	2.655*** (0.0242)	2.644*** (0.0242)
Observations	573,108	573,108	573,108
R-squared	0.015	0.015	0.015
Number of id	98,717	98,717	98,717

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

Control variables suppressed

**Table 3.3:** Baseline Model: Principal Component Measure

VARIABLES	(1) lnWage	(2) lnWage	(3) lnWage
NewHire*U	-0.00210*** (0.000622)	-0.00213*** (0.000623)	-0.00103 (0.000891)
NewHire	0.00677* (0.00373)	0.00648* (0.00374)	0.00841 (0.00552)
U	-0.00322*** (0.000419)	-0.00306*** (0.000425)	-0.00145*** (0.000502)
Mismatch <sup>PC</sup>		0.000997 (0.000619)	0.00733*** (0.00119)
NewHire*Mismatch <sup>PC</sup>			-0.00216 (0.00158)
Mismatch <sup>PC</sup> *U			-0.00108*** (0.000225)
NewHire*Mismatch <sup>PC</sup> *U			-8.46e-05 (0.000278)
Constant	2.660*** (0.0241)	2.658*** (0.0242)	2.649*** (0.0242)
Observations	573,108	573,108	573,108
R-squared	0.015	0.015	0.015
Number of id	98,717	98,717	98,717

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

Control variables suppressed

**Table 3.4:** Baseline Model: Directional and Non-Directional Individual Component Measures

VARIABLES	(1a) lnWage	(1b) lnWage	(2a) lnWage	(2b) lnWage	(3a) lnWage	(3b) lnWage
NewHire*U	-0.00202*** (0.000621)	-0.00156** (0.000786)	-0.00204*** (0.000620)	-0.00149* (0.000797)	-0.00205*** (0.000622)	-0.00117 (0.000828)
OneSided <sup>PC</sup> *U	0.000551** (0.000230)					
TwoSided <sup>PC</sup> *U		-0.000672*** (0.000246)				
OneSided <sup>PC</sup> *U			0.000226 (0.000214)			
TwoSided <sup>PC</sup> *U				-0.00133*** (0.000218)		
OneSided <sup>PC</sup> *U					0.000710*** (0.000200)	
TwoSided <sup>PC</sup> *U						-0.000630*** (0.000207)
Component Measure	High-skill One-Sided	High-skill Two-Sided	Mid-skill One-Sided	Mid-skill Two-Sided	Low-skill One-Sided	Low-skill Two-Sided
Observations	573,108	573,108	573,108	573,108	573,108	573,108
R-squared	0.018	0.015	0.018	0.015	0.015	0.015
Number of id	98,717	98,717	98,717	98,717	98,717	98,717

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Other variables, interactions, and controls suppressed



**Table 3.5:** Extended Model: Euclidean Distance Measure

VARIABLES	(1) lnWage	(2) lnWage	(3) lnWage
NewHireEE*U	-0.00245*** (0.000695)	-0.00257*** (0.000696)	-0.00110 (0.00104)
NewHireNE*U	-0.00125 (0.00132)	-0.00138 (0.00132)	-0.00208 (0.00227)
NewHireEE	0.0144*** (0.00418)	0.0143*** (0.00419)	0.0130* (0.00666)
NewHireNE	-0.0159** (0.00776)	-0.0161** (0.00776)	0.00681 (0.0142)
U	-0.00323*** (0.000419)	-0.00295*** (0.000429)	-0.00115** (0.000495)
Mismatch		0.00153** (0.000654)	0.00870*** (0.00117)
NewHireEE*Mismatch			-0.00179 (0.00188)
NewHireNE*Mismatch			-0.00901** (0.00402)
Mismatch*U			-0.00114*** (0.000200)
NewHireEE*Mismatch*U			-6.46e-05 (0.000300)
NewHireNE*Mismatch*U			0.000621 (0.000641)
Constant	2.660*** (0.0241)	2.655*** (0.0242)	2.643*** (0.0242)
Observations	573,108	573,108	573,108
R-squared	0.015	0.015	0.016
Number of id	98,717	98,717	98,717

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

Control variables suppressed

**Table 3.6:** Extended: Principal Component Measure

VARIABLES	(1) lnWage	(2) lnWage	(3) lnWage
NewHireEE*U	-0.00245*** (0.000695)	-0.00248*** (0.000695)	-0.00121 (0.000989)
NewHireNE*U	-0.00125 (0.00132)	-0.00129 (0.00132)	-0.000366 (0.00203)
NewHireEE	0.0144*** (0.00418)	0.0141*** (0.00419)	0.0122** (0.00613)
NewHireNE	-0.0159** (0.00776)	-0.0162** (0.00776)	-0.00549 (0.0122)
U	-0.00323*** (0.000419)	-0.00307*** (0.000425)	-0.00148*** (0.000502)
Mismatch <sup>PC</sup>		0.00101 (0.000619)	0.00727*** (0.00119)
NewHireEE*Mismatch <sup>PC</sup>			-0.00101 (0.00178)
NewHireNE*Mismatch <sup>PC</sup>			-0.00447 (0.00341)
Mismatch <sup>PC</sup> *U			-0.00108*** (0.000225)
NewHireEE*Mismatch <sup>PC</sup> *U			-0.000121 (0.000310)
NewHireNE*Mismatch <sup>PC</sup> *U			-8.49e-05 (0.000610)
Constant	2.660*** (0.0241)	2.657*** (0.0242)	2.648*** (0.0242)
Observations	573,108	573,108	573,108
R-squared	0.015	0.015	0.016
Number of id	98,717	98,717	98,717

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

Control variables suppressed

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