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UNIVERSITY OF CALIFORNIA, SAN DIEGO

**Essays on Frictions in Financial Macroeconomics**

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

in

Economics

by

Benjamin S. Kay

Committee in charge:

Professor Marjorie Flavin, Chair  
Professor Bruce Lehmann  
Professor Harry Markowitz  
Professor Valerie Ramey  
Professor Allan Timmermann

2012

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The dissertation of Benjamin S. Kay 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

2012

## DEDICATION

To my wife Margery for her outside-the-classroom lessons on complementarities in production and consumption, sunk costs, repeated games, and much more, my daughter Gila for convincing me that the bequest motive is a real and powerful force in human affairs, and to my parents, without whom none of this would have been possible.

## EPIGRAPH

*I am nothing but skin and bones; I have escaped with only the skin of my teeth.*

— Job 19:20

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Chapter 3 represents coauthored work with Thomas Daula. The dissertation author and Thomas Daula are co-first-authors.

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Consumption, Saving, Production, Employment, and Investment (E2)

Secondary Field: Financial Economics

Corporate Finance and Governance (G3)

ABSTRACT OF THE DISSERTATION

**Essays on Frictions in Financial Macroeconomics**

by

Benjamin S. Kay

Doctor of Philosophy in Economics

University of California, San Diego, 2012

Professor Marjorie Flavin, Chair

Building on Flavin and Nakagawa (2008), chapter one models household optimal consumption and portfolio selection when consumption services are generated by both housing and non-housing consumption. Housing is illiquid in that a non-convex adjustment cost must be paid when it is sold. It is shown that optimal consumption of housing is not a constant fraction of wealth but instead depends on the ratio of wealth to housing and the price of housing. Households adjust housing infrequently, waiting for large wealth changes before adjustment. As in models without this adjustment cost, households adjust non-housing consumption each period. Unlike in frictionless models, non-housing consumption is not a constant fraction of wealth. For particular parameters of the utility function and asset markets drawn from the literature, model simulations match aggregate consumption dynamics better than alternative frictionless models, even

those with homes as assets. The simulations also predict differing responses of households with different fractions of their wealth in housing.

In chapter two, stock market makers are afraid that informed insiders will take advantage of them in trade. To protect themselves, they may increase the bid-offer spread to include a fee for the adverse selection risk. If set correctly, market makers will share in profits from others trading on private information and can distribute the remaining costs among other market participants. If market makers protect themselves this way, then when the risk of informed trading is relatively low, the bid-offer spread should decline. The risk of informed trading will be relatively low when the difference in public and private information shrinks. Filings with the Securities and Exchange Commission (SEC) and conference calls where corporate earnings are announced and discussed should be events that diminish this difference. Because smaller companies attract less scrutiny, they may experience relatively larger changes in this information distance after these releases. This paper finds weak evidence that spreads diminish when this information is released and a weak size effect. It hypothesizes that the bid-offer spread seems to be unresponsive to information and company size because the adverse selection component of the spread is smaller than has previously been estimated does or possibly does not exist. Estimates of this spread are actually a statistical illusion created by the structural form of earlier estimation techniques.

The recent global financial crisis suggests the post-1984 Great Moderation has come to an abrupt end. How we obtained nearly 25 years of stability and why it ended are ongoing puzzles. Chapter three depart from traditional monetary policy explanations and consider two empirical regularities in US employment: i) the decline in the procyclicality of labor productivity with respect to output and labor input and ii) the increase in the volatility of labor input relative to output. We first consider whether these stylized facts are robust to statistical methodology. We find that the widely reported decline in the procyclicality of labor productivity with respect to output is fragile. Using a new international data set on total hours constructed by Ohanina and Raffo (2011) we then consider whether these moments are stylized facts of the global Great Moderation. We document significant international heterogeneity. We then investigate whether the role of labor market frictions in the US as found in Galí and van Rens (2010) can explain the

international results. We conclude that their stylized model does not appear to account for the differences with the US experience and suggest a direction for future research.



# Chapter 1

## The Effects of Housing Adjustment Costs on Consumption Dynamics

### 1.1 Introduction

The Great Recession and subsequent slow recovery have highlighted the serious macroeconomic consequences of problems in housing markets. Housing related industries like construction, furniture, real estate sales, and home improvement have suffered worse than the economy as a whole.<sup>1</sup> National home price declines of 30% have left an estimated fifteen million households with negative home equity and the mortgage delinquency rate five times its historical average.<sup>2, 3</sup> Surprisingly, amidst this loss of wealth and employment, non-durable consumption (hereafter just consumption) was essentially unchanged.

It is surprising in part because home ownership is at the center of household assets and liabilities. Of the households participating in the Federal Reserve Board's 2007

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<sup>1</sup>Leamer (2007) details the outsized role of housing in most post W.W. II recessions. Goodman and Mance (2011) document the 2007-2009 fall in employment in the construction industry was more severe than other post-war recessions. The U.S. Bureau of Economic Analysis of Value Added by (NAICS) Industry documents that furniture and related products economic value added fell by a third from 2006 to 2009. The California Department of Real Estate's Licensee/Examinee Statistics for Fiscal Year 2010/2011 shows a 20% decline in the number of licensed real estate agents from 2007 to 2010.

<sup>2</sup>How to Stop the Drop in Home Values Martin Feldstein, p. A29 10/12/11, The New York Times

<sup>3</sup>Board of Governors of the Federal Reserve System, FRED Economic Data, Delinquency Rate On Single-Family Residential Mortgages 2010 compared to 1990-2006 average.

Survey of Consumer Finances (SCF), 69% owned their own home.<sup>4</sup> Among homeowners, housing is typically their largest asset. The median percentage of net worth accounted for by their primary residence is 84%. Debts on the home also are typically the household's largest liability. The median percentage of household debt secured by the primary residence is 90%. Falling home prices and fixed liabilities suggest that home-owning households should have seen large declines in their net worth since 2006, even if homeowners did not invest in the financial markets. In many models of the household's basic decision over consumption and investment it is optimal to chose them proportionally to wealth (e.g., Merton (1969) and Constantinides (1986)) and therefore, a large wealth effect on consumption might be expected.

It is also surprising that changes in home values have had little effect on consumption because housing services are a large part of household spending. According to the Bureau of Economic Analysis's 2011 National Income and Product Accounts (NIPA), Housing and Utility Services is the second (at 18% to Non-durable Consumption's 23%) largest category of personal expenditures. This aggregate hides even more exceptional cross-sectional importance. The U.S. Department of Housing and Urban Development estimates that 11% of households spend 50% or more of their annual income on housing. As long as housing is a normal good (and Hanushek and Quigley (1980) provides evidence that it is), then the substitution effect will exacerbate the wealth effect to reduce consumption. Households will substitute out of consumption goods and into the now cheaper housing.

This paper resolves much of this anomaly by introducing a non-convex transaction cost for changing holdings of housing into the household's basic problem of allocating consumption optimally over time in a world with uncertainty in asset returns. To adjust housing, households must pay an adjustment cost equal to a fixed fraction of their home's value. This represents the costs to the household of selling a home and moving their possessions. Two other key features of housing are replicated. First, housing acts as a risky asset on the household balance sheet. Second, housing is in the utility function. Housing provides housing services as shelter and by complementing

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<sup>4</sup>Of all other financial and real assets only transaction accounts (e.g., checking accounts) are more common.

consumption.<sup>5</sup> This respectively captures that people prefer larger bedrooms and that it is easier to cook a large meal in large kitchen.

These features generate different predictions of consumption, investment, and value functions than models without housing or with housing but lacking housing frictions. Households make infrequent and large housing adjustments but frequent and mostly small consumption changes. Because of this, the marginal utility of consumption depends on current housing (relative to wealth). In this specification it is optimal to have relatively high consumption when house holdings are large relative to wealth. Therefore, when households experience negative wealth shocks they reduce consumption by much less than their reduction in wealth unless the shock induces them to move. This friction also causes households to have preferences over risk that depend upon current housing (relative to wealth). Households that have just adjusted their housing are more risk averse. Households near the adjustment bounds (determined by where households have so much or little housing they move) are relatively risk tolerant. This changes the curvature of the value function to be less curved (in an Arrow-Pratt relative risk aversion sense) than without the friction near the adjustment bounds but more curved for those who have just moved.

This paper contributes to two principle fields in macroeconomic literature. The first studies the use of housing in macroeconomic models. This is the first paper in that literature to contain housing, housing frictions, non-durable consumption, and estimates of consumption and investment policy functions. The second studies the excess smoothness of aggregate consumption with respect to fluctuations in observable wealth. While housing has been used to study this problem before, this paper is the first to investigate the effect of housing on consumption dynamics when frictions and non-durable goods are also modeled.

Henderson and Ioannides (1983) provides an early theoretical presentation integrating housing and non-durable consumption. Goulder (1989) considers housing as an investment asset but uses a rental services model to abstract away from how the stock of housing enters household utility. Berkovec and Fullerton (1992) integrates these asset and utility approaches, injecting housing into the consumption and investment decisions.

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<sup>5</sup>This need not be solely the utility value of living in a bigger home. It might also be a reduced form representation of how housing services complement home production and leisure.

This approach was widely adopted. For example, Lustig and Nieuwerburgh (2005) and Piazzesi et al. (2007) are respectively partial equilibrium and general equilibrium models employing this approach. This is a budget share theory of housing importance because it justifies an emphasis on housing because of its large share of consumption and investment.

There is an alternative perspective, acknowledging that the budget share theory is important but focusing on the significant frictions in trade of housing. Topel and Rosen (1988) models housing as an asset facing convex adjustment costs. Grossman and Laroque (1990a) introduces a more realistic non-convex adjustment cost for durable consumption, the only consumption in the model. Flavin and Nakagawa (2008) extends Grossman and Laroque with non-durable consumption and housing price dynamics. This allows for richer adjustment behavior by households and for asset prices to be consistent with the consumption-beta model of Breeden (1979) and Lucas (1978). Flavin and Nakagawa cannot solve for the consumption and investment policy functions and so do not address individual and aggregate consumption dynamics. This paper solves for the policy functions of a related model and therefore can address questions about aggregate consumption and investment that they could not.

Mehra and Prescott (1985) identified the anomalous relationship between volatile asset markets and smooth consumption data. This paper builds upon the literature of possible explanations.<sup>6</sup> By integrating housing services into the utility function, it alters household preferences. Other important preference modification solutions include Epstein and Zin (1989) and Constantinides (1990). Mehra (2007) and Dynan (2000) provide empirical evidence that these alternative preference modifications cannot resolve the anomaly with realistic preference parameters.

Including incomplete markets or missing assets in the household portfolio can resolve the anomaly. Mehra and Prescott (1985) speculates that omitted human capital may explain the anomaly.<sup>7</sup> Guiso et al. (1996) finds that a combination of income risk, health risk, and borrowing constraints on labor income can explain one quarter of the anomaly. Appendix B considers a simple extension to the model that integrates hu-

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<sup>6</sup>See Mehra (2007) for a survey of the enormous literature of possible complete and partial solutions.

<sup>7</sup>This is analogous to the Roll critique from Roll (1977). If the observed portfolio is not the market portfolio then observed portfolio dynamics need not predict consumption dynamics.

man capital. This paper confirms that housing is an important asset to include in the household portfolio, especially when incorporated with realistic frictions.

Fixing improper modeling of assets in the portfolio also can resolve the anomaly. Rietz (1988) and Barro (2006) both make use of low probability but severe and (in expectation) permanent wealth shocks to depress household equity holdings and consumption response to asset returns. However, on realistic disaster magnitudes only part of the anomaly is resolved. Though this paper does not address disasters explicitly, it does model asset returns at a yearly frequency which allows for more extreme movements in the wealth portfolio between portfolio adjustments. In a single year, the model allows for -30% stock market returns and -14% housing market returns. Mehra et al. (2011) sensibly points out that borrowing and lending rates are not the same, and much of what looks like an equity premium is in fact the costs of financial intermediation. The household's optimal investment policy makes all households (weakly) net-borrowers. Therefore the model uses borrowing rates based on mortgage rates rather than a lending rates based on risk-free bonds.

The rest of the paper is organized as follows. Section 1.2 describes the model and lays out a transformation that reduces the dimensionality of the problem. Section 1.3 describes the computational techniques used to solve the problem. Section 1.4 discusses the parameter values that describe household preferences, adjustment costs, and the parametric assumptions about asset returns. Section 1.5 shows the solution to the value and policy functions of the model laid out in Section 1.2. It also examines the aggregate consumption dynamics predicted by the model and contrasts them with alternative frictionless models and NIPA measured true consumption. Section 1.6 concludes.

## 1.2 Model

The model is a simplified version of Flavin and Nakagawa (2008). The principal simplification is to abstract from multiple housing markets to a single risky housing market. An additional difference is that Flavin and Nakagawa model the household decision in continuous time while this paper does so in discrete time. Adapting the problem to discrete time also requires changes to housing and risky asset return processes.

### 1.2.1 Budget Constraint and the Evolution of the Wealth Equation

Let  $B_t$ ,  $X_t$ , and  $P_t \cdot H_t$  respectively denote the amounts (in units of non-durable consumption) of risk-free, risky, and housing assets chosen by the consumer at time  $t$ .<sup>8</sup> Since this is the exhaustive set of assets in the model, household wealth  $W_t$  is defined as follows:

$$W_t \equiv R_f \cdot B_{t-1} + R_{m,t} \cdot X_{t-1} + P_t \cdot H_{t-1}$$

where  $R_f$  is the gross return of a risk-free asset between  $t-1$  and  $t$ ,  $R_{m,t}$  is the realized gross return of a risky asset between  $t-1$  and  $t$ , and  $P_t$  is the price of square feet of housing in units of consumption at time  $t$ . The household then allocates this stock of wealth among consumption and savings to satisfy the budget constraint<sup>9</sup>:

$$W_t = C_t + \mathbf{1}_{\{H_t \neq H_{t-1}\}} \cdot \lambda \cdot H_{t-1} \cdot P_t + B_t + X_t + H_t \cdot P_t$$

We also can rewrite this in the form of Assets - Savings = Consumption:

$$(R_f \cdot B_{t-1} + R_{m,t} \cdot X_{t-1} + P_t H_{t-1}) - (B_t + X_t + H_t \cdot P_t) = C_t + \mathbf{1}_{\{H_t \neq H_{t-1}\}} \cdot \lambda \cdot H_{t-1} \cdot P_t$$

<sup>8</sup>Instead of a single risky asset, without loss of generality this could be a mean-variance efficient portfolio of risky assets uncorrelated with housing returns.

<sup>9</sup>This may seem like an odd budget constraint. The following derivation may provide some insight. A budget constraint shows Existing Assets + Income = Consumption + Savings. In the terms of this model, existing assets are the holdings from the last period are  $B_{t-1} + X_{t-1} + P_{t-1} H_{t-1}$ . Income (think dividend, capital gains, and interest income in this paper) is the returns on those assets  $r_f \cdot B_{t-1} + r_{m,t} \cdot X_{t-1} + (P_t - P_{t-1}) H_{t-1}$ . These resources must equal the two expenditures categories. The first is consumption of non-durable goods and services  $C_t$  and housing adjustment costs  $\mathbf{1}_{\{H_t \neq H_{t-1}\}} \cdot \lambda \cdot H_{t-1} P_t$ . All other wealth is allocated to investments in bonds, risky assets, and housing totaling  $B_t + X_t + H_t \cdot P_t$ . Defining  $r_f$  and  $r_{m,t}$  and the net return analogs to  $R_f$  and  $R_{m,t}$  respectively we get the following budget constraint:

$$\begin{aligned} & (B_{t-1} + X_{t-1} + P_{t-1} H_{t-1}) + (r_f \cdot B_{t-1} + r_{m,t} \cdot X_{t-1} + (P_t - P_{t-1}) H_{t-1}) \\ &= (C_t + \mathbf{1}_{\{H_t \neq H_{t-1}\}} \cdot \lambda \cdot H_{t-1} P_t) + (B_t + X_t + H_t \cdot P_t) \end{aligned}$$

Combining terms, the left-hand side is just  $W_t$  as defined above

$$\begin{aligned} R_f \cdot B_{t-1} + R_{m,t} \cdot X_{t-1} + P_t H_{t-1} &= C_t + B_t + X_t + (H_t + \mathbf{1}_{\{H_t \neq H_{t-1}\}} \cdot \lambda \cdot H_{t-1}) \cdot P_t \\ W_t &= \end{aligned}$$

Using the definition of state variable  $W_t$  to substitute out the bond control variable ( $B_t$ ) we combine the definition of  $W_{t+1}$  and the budget constraint:

$$\begin{aligned} W_{t+1} &= R_f \cdot B_t + R_{m,t+1} \cdot X_t + P_{t+1} H_t \\ &= R_f \cdot (W_t - C_t - X_t - (H_t + \mathbf{1}_{\{H_t \neq H_{t-1}\}} \cdot \lambda \cdot H_{t-1}) \cdot P_t) + R_{m,t+1} \cdot X_t + P_{t+1} \cdot H_t \end{aligned}$$

. This can be simplified by distributing and collecting terms:

$$\begin{aligned} W_{t+1} &= R_f \cdot (W_t - C_t) + (R_{m,t+1} - R_f) \cdot X_t \\ &\quad + \left( P_{t+1} - R_f \cdot P_t \cdot \left( 1 + \mathbf{1}_{\{H_t \neq H_{t-1}\}} \cdot \lambda \cdot \frac{H_{t-1}}{H_t} \right) \right) H_t \end{aligned}$$

This is the evolution of wealth equation which depends on the state variables  $W_t$ ,  $H_{t-1}$ , and  $P_t$ , the control variables  $X_t$ ,  $H_t$ , and  $C_t$ , and the random variables  $P_{t+1}$ ,  $R_f$ , and  $R_{m,t+1}$ .

## 1.2.2 Felicity and Value Functions

The household felicity function is in constant elasticity of substitution (CES) form, taking as arguments non-durable consumption and units of housing:

$$U(C_t, H_t) = \frac{(C_t^\alpha + \gamma \cdot H_t^\alpha)^{\frac{1-\rho}{\alpha}}}{1-\rho}$$

The rate of substitution between non-durable and durable consumption is controlled by  $\alpha$ . The parameter  $\gamma$  converts the units of housing as measured by  $P_t$  in the budget constraint into the units of housing consumed by the household (see Appendix A for a full discussion). In frictionless models, the parameter  $1 - \rho$  controls the elasticity of inter-temporal substitution (EIS) and the curvature of the both the value function and the felicity function. In this model,  $\rho$  controls only the curvature of the felicity function.

Let  $V(W_t, H_{t-1}, P_t)$  be the supremum of the expected utility that the consumer

can achieve from initial conditions  $(W_t, H_{t-1}, P_t)$ . Then  $V(W_t, H_{t-1}, P_t)$  satisfies the following Bellman equation:

$$V(W_t, H_{t-1}, P_t) = \sup_{C_t, X_t, H_t} \left[ \frac{(C_t^\alpha + \gamma H_t^\alpha)^{\frac{1-\rho}{\alpha}}}{1-\rho} + \beta \mathbb{E}_t [V(W_{t+1}, H_t, P_{t+1})] \right]$$

Define  $\Phi$  as follows:

$$\Phi \equiv -\ln(\beta) - (1-\rho) \cdot (R_f - 1) - \frac{(\mathbb{E}[R_{m,t+1} - 1])^2}{2 \cdot \text{Var}(R_{m,t+1})} \cdot \frac{1-\rho}{\rho}$$

Grossman and Laroque 1990 show that if  $\Phi > 0$  then the value function in this problem is homogeneous in  $H_{t-1}$  and  $W_t$  of degree  $1-\rho$ . For the parameters used in this paper, this condition holds and  $H_{t-1}^{1-\rho} \cdot V\left(\frac{W_t}{H_{t-1}}, 1, P_t\right) = V(W_t, H_{t-1}, P_t)$ . Therefore, we can rewrite the Bellman as follows:

$$\begin{aligned} & H_{t-1}^{1-\rho} \cdot V\left(\frac{W_t}{H_{t-1}}, 1, P_t\right) \\ &= \sup_{C_t, X_t, H_t} \left[ \frac{\left(\left(\frac{C_t}{H_{t-1}}\right)^\alpha + \gamma \cdot \left(\frac{H_t}{H_{t-1}}\right)^\alpha\right)^{\frac{1-\rho}{\alpha}} \cdot H_{t-1}^{1-\rho}}{1-\rho} + \beta \cdot H_t^{1-\rho} \cdot \mathbb{E}_t \left[ V\left(\frac{W_{t+1}}{H_t}, 1, P_{t+1}\right) \right] \right] \end{aligned}$$

### 1.2.3 Transforming the Problem with Housing Intensive State and Control Variables

Now define housing intensive variables that scale the state and control variables by  $H_{t-1}$ :

$$\begin{array}{cccc} W_t & H_t & X_t & C_t \\ \downarrow & \downarrow & \downarrow & \downarrow \\ y_t \equiv \frac{W_t}{H_{t-1}} - \lambda \cdot P_t & h_t \equiv \frac{H_t}{H_{t-1}} & x_t \equiv \frac{X_t}{X_{t-1}} & c_t \equiv \frac{C_t}{H_{t-1}} \end{array}$$



Simplify the value function and substitute the intensive variables:

$$V(y_t + \lambda \cdot P_t, 1, P_t) = \sup_{c_t, x_t, h_t} \left[ \frac{(c_t^\alpha + \gamma \cdot h_t^\alpha)^{\frac{1-\rho}{\alpha}}}{1-\rho} \right. \\ \left. + \beta \cdot h_t^{1-\rho} \cdot \mathbb{E}_t [V(y_{t+1} + \lambda \cdot P_{t+1}, 1, P_{t+1})] \right]$$

Simplify the problem further by defining  $G(y_t, P_t) \equiv V(y_t + \lambda \cdot P_t, 1, P_t)$  and make that substitution as follows:

$$G(y_t, P_t) = \sup_{c_t, x_t, h_t} \left[ \frac{(c_t^\alpha + \gamma \cdot h_t^\alpha)^{\frac{1-\rho}{\alpha}}}{1-\rho} + \beta \cdot h_t^{1-\rho} \cdot \mathbb{E}_t [g(y_{t+1}, P_{t+1})] \right]$$

Then take the evolution of wealth equation and write it in intensive form into an equation of the evolution of  $y_t$

$$W_{t+1} = R_f \cdot (W_t - C_t) + (R_{m,t+1} - R_f) \cdot X_t \\ + \left( P_{t+1} - R_f \cdot P_t \cdot \left( 1 + \mathbf{1}_{\{H_t \neq H_{t-1}\}} \cdot \lambda \cdot \frac{H_{t-1}}{H_t} \right) \right) H_t$$

From the definition of  $y_t$ :

$$y_{t+1} = \frac{W_{t+1}}{H_t} - \lambda \cdot P_{t+1}$$

. Use the evolution of wealth equation to substitute out  $W_{t+1}$ :

$$y_{t+1} = \frac{H_{t-1}}{H_t} \cdot \left[ \frac{R_f \cdot (W_t - C_t) + (R_{m,t+1} - R_f) \cdot X_t}{H_{t-1}} \right. \\ \left. + \frac{\left( P_{t+1} - R_f \cdot P_t \cdot \left( 1 + \mathbf{1}_{\{H_t \neq H_{t-1}\}} \cdot \lambda \cdot \frac{H_{t-1}}{H_t} \right) \right) H_t}{H_{t-1}} \right] - \lambda \cdot P_{t+1}$$

. Replace  $(C_t, X_t, H_t)$  with their intensive forms  $(c_t, x_t, h_t)$ :

$$= \frac{R_f \cdot \left( \frac{W_t}{H_{t-1}} - c_t \right) + (R_{m,t+1} - R_f) \cdot x_t}{h_t} + P_{t+1} - R_f \cdot P_t \cdot \left( 1 + \frac{\mathbf{1}_{\{H_t \neq H_{t-1}\}} \cdot \lambda}{h_t} \right) - \lambda \cdot P_{t+1}$$

. Add and subtract  $\lambda \cdot P_t$  from the first parentheses:

$$= R_f \cdot \frac{\left( \frac{W_t}{H_{t-1}} - c_t + \mathbf{1}_{\{H_t \neq H_{t-1}\}} \cdot \lambda \cdot P_t + \lambda \cdot P_t - \lambda \cdot P_t \right)}{h_t} + (R_{m,t+1} - R_f) \cdot \frac{x_t}{h_t} + P_{t+1} - R_f \cdot P_t - \lambda \cdot P_{t+1}$$

. Replace  $\frac{W_t}{H_{t-1}} - \lambda \cdot P_t$  with  $y_t$ :

$$= R_f \cdot \frac{(y_t - c_t + (\mathbf{1}_{\{H_t \neq H_{t-1}\}} - 1) \cdot \lambda \cdot P_t)}{h_t} + (R_{m,t+1} - R_f) \cdot \frac{x_t}{h_t} + P_{t+1} \cdot (1 - \lambda) - R_f \cdot P_t$$

. Simplify by replacing  $\mathbf{1}_{\{H_t \neq H_{t-1}\}} - 1$  with  $\mathbf{1}_{\{h_t=1\}}$ :

$$= R_f \cdot \frac{y_t - c_t + \mathbf{1}_{\{h_t=1\}} \cdot \lambda \cdot P_t}{h_t} + (R_{m,t+1} - R_f) \cdot \frac{x_t}{h_t} + P_{t+1} \cdot (1 - \lambda) - R_f \cdot P_t$$

$$\Rightarrow y_{t+1} = R_f \cdot \frac{y_t - c_t + \mathbf{1}_{\{h_t=1\}} \cdot \lambda \cdot P_t}{h_t} + (R_{m,t+1} - R_f) \cdot \frac{x_t}{h_t} + P_{t+1} \cdot (1 - \lambda) - R_f \cdot P_t$$

. Substitute the equation for  $y_{t+1}$  into the transformed Bellman:

$$G(y_t, P_t) = \sup_{c_t, x_t, h_t} \left[ \frac{(c_t^\alpha + \gamma \cdot h_t^\alpha)^{\frac{1-\rho}{\alpha}}}{1-\rho} + \beta \cdot h_t^{1-\rho} \cdot \mathbb{E}_t [g(y_{t+1}, P_{t+1})] \right]$$

$$\begin{aligned}
&= \sup_{c_t, x_t, h_t} \left[ \frac{(c_t^\alpha + \gamma \cdot h_t^\alpha)^{\frac{1-\rho}{\alpha}}}{1-\rho} + \beta \cdot h_t^{1-\rho} \cdot \mathbb{E}_t \left[ G \left( R_f \cdot \frac{y_t - c_t + \mathbf{1}_{\{h_t=1\}} \cdot \lambda \cdot P_t}{h_t} \right. \right. \right. \\
&\quad \left. \left. \left. + (R_{m,t+1} - R_f) \cdot \frac{x_t}{h_t} + P_{t+1} \cdot (1 - \lambda) - R_f \cdot P_t, P_{t+1} \right) \right] \right]
\end{aligned}$$

This problem has two states:  $y_t$  and  $P_t$ , three controls:  $c_t$ ,  $x_t$ , and  $h_t$ , and two random processes:  $P_{t+1}$  and  $R_{m,t+1}$ . One state and one control have been eliminated from the original problem. This transformed problem is solved computationally in Section 1.5. Though the transformed variables may sometimes have less intuitive interpretations, the reduced dimensionality substantially eases solving the problem computationally.

### 1.3 Computational Modeling

This problem of two states  $(y_t, P_t)$  and three controls  $(c_t, x_{t+1}, h_{t+1})$  does not have a closed-form solution. However, it can be solved with computational techniques. The general approach is value function iteration with a discretized state and adaptive grid policy space. Judicious use of Howard's improvement step speeds up the convergence of the value function. After reaching convergence with discrete policy choices, a more accurate value function is generated by allowing policy choices to be continuous. The global optimization method Pattern Search is employed to find the optimal policies and calculate the value function.<sup>10</sup> Final iteration tolerances are within machine precision.

This paper accounts for stochastic returns with discrete approximations to historical returns. For stock market returns, the method of Tauchen (1986) is employed. Specifically, this paper uses six states to approximate the returns of the stock market. The housing price process is described with a 15 state transition matrix. Conditional on today's price  $P_t$ , no more than five future prices  $P_{t+1}$  have positive probability. The stock market return and housing price processes are depicted in Tables 1.1 and 1.2, respectively. In keeping with the findings of Flavin and Nakagawa (2008) that found the correlation between housing and stock returns was effectively zero, this paper assumes

<sup>10</sup>Implemented in Matlab's Global Optimization Toolkit and detailed in Kolda et al. (2003).

**Table 1.1:** Tauchen Method Applied to Stock Returns from 1950-2009

Real Stock Market Return	Probability of Outcome
-29.8%	4.82%
-14.3%	15.5%
1.11%	29.7%
16.6%	29.7%
32.0%	15.5%
47.5%	4.82%
Predicted / Actual (1950-2010) Real Mean Return	8.8% / 8.8%
Predicted / Actual (1950-2010) Return Standard Deviation	18.6% / 18.6%

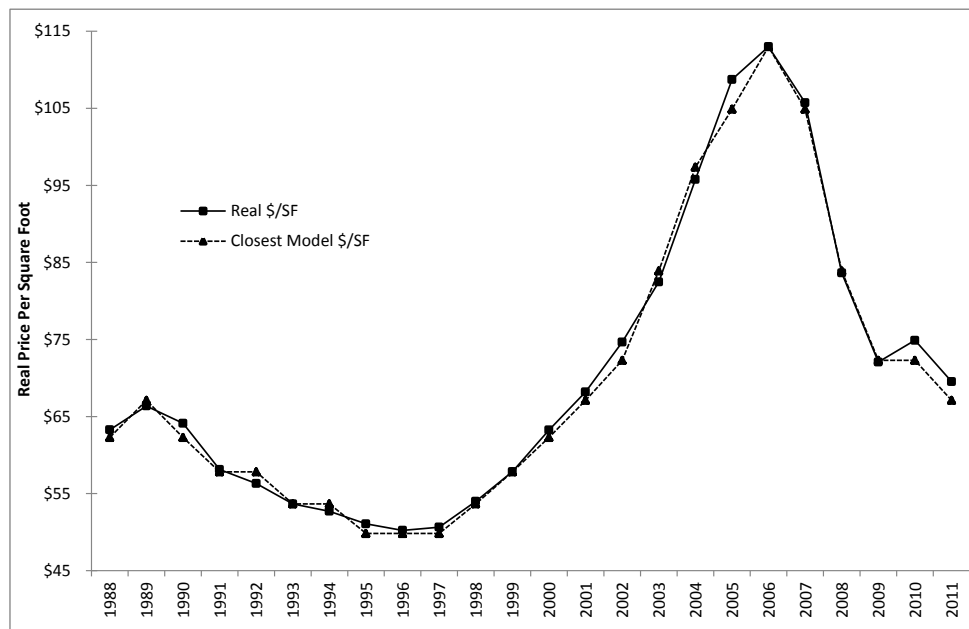
Source: Stock market returns from Fama-French U.S. Research Returns Data (1950-2010). Inflation from the Bureau of Labor Statistics' Consumer Price Index - All Urban Consumers series.

that housing and risky asset returns are independent.

The distribution of annual stock market real returns is calibrated from Fama-French market return data (deflated with the CPI, pre-tax, and net of dividends) to match the mean and variance of returns from 1950-2010. The distribution of housing returns is calibrated on the Case-Shiller 10-city Index (deflated with the CPI and pre-tax, hereafter CS10) to match the mean, variance, and skew of the historical returns from 1987-2010. The range of housing states (depicted in table 1.2) allows for housing price states above peak real prices in 2006 and below trough prices in 1995. Figure 1.1 graphs the historical prices of the CS10 against the model implied price process. In general, the fit is good. The largest gap is less than  $3 \frac{\$}{Ft^2}$  which is small relative to regional and inter-temporal variations in prices per square foot.

Individual households face idiosyncratic home price risk as well. Unfortunately, the literature finds disparate estimates of the idiosyncratic home price risk. Bourassa et al. (2005) found the standard deviation of individual home prices is 1.2-2.6 times that of the standard deviation of the whole market in New Zealand. Goetzmann (1993) found a range of 1.5 to 3 for four U.S. cities. On the higher end, Englund et al. (2002) found this ratio to be 5.7 in Sweden. This is analogous (but not identical given differing time series properties) to the true variance of household prices being  $\sigma_{House}^2 \in \sigma_{Case-Shiller}^2 \cdot [1.2, 5.7]$  in this model.

Because the cross-sectional and time-series nature of idiosyncratic component



**Figure 1.1:** Model Implied Price Process Approximates The Real Price History

**Table 1.2:** A 15 State Markov Model of Home Price Dynamics

$P_t \backslash P_{t+1}$	\$46	\$50	\$54	\$58	\$62	\$67	\$72	\$78	\$84	\$90	\$97	\$105	\$113	\$122	131
\$46	.44	.51	.05												
\$50	.26	.18	.51	.05											
\$54	.21	.05	.18	.51	.05										
\$58		.21	.05	.18	.51	.05									
\$62			.21	.05	.18	.51	.05								
\$67				.21	.05	.18	.51	.05							
\$72					.21	.05	.18	.51	.05						
\$78						.21	.05	.18	.51	.05					
\$84							.21	.05	.18	.51	.05				
\$90								.21	.05	.18	.51	.05			
\$97									.21	.05	.18	.51	.05		
\$105										.21	.05	.18	.51	.05	
\$113											.21	.05	.18	.51	.05
\$122												.21	.05	.18	.56
\$131													.21	.05	.74

$R_{H,t+1}$	True	Model ( $P_t = 113$ )
Mean	1.015	1.015
Variance	.00875	.0087
Skew	-0.6510	-0.6510

Source: The Standard & Poor's Case-Shiller 10-city Home Price Index from 1987-2010. Inflation from the Bureau of Labor Statistics' Consumer Price Index - All Urban Consumers series.

of house prices is not well understood, this paper uses aggregate house price dynamics only. Sensitivity testing of the simulation shows that greater price risk lowers portfolio holdings of the risky and housing assets, thereby decreasing sensitivity of non-durable consumption to home price movements. This is consistent with Heaton and Lucas (2000) that finds that households facing idiosyncratic risks decrease their holdings of risky assets. Either way, treating this greater risk as an increased aggregate housing price risk or an idiosyncratic price risk would make household wealth less sensitive to asset price movements. Through this mechanism, the simulation results of consumption dynamics would be further dampened with respect to the frictionless models. Therefore, the assumption that households face no idiosyncratic price risk is a conservative one that reduces the model fit.

## 1.4 Simulation Parameters

The simulation uses preference parameter estimates from Flavin and Nakagawa (2008).

$$\gamma = 1 \quad \rho = 1.8 \quad \beta = .98 \quad \alpha = -6.7$$

A rho parameter of 1.8 is well within laboratory experiments of relative risk aversion over lotteries (and consistent the findings of Szpiro (1986) from insurance data). Though the right inter-temporal discount rate is still much debated,  $\beta = .98$  seems reasonable for a simulation at annual frequencies.<sup>11</sup> Readers may not intuit on the sensibility of the choice of  $\gamma$ . Appendix A shows that the purpose of  $\gamma$  is to primarily convert between the units of of housing determining utility (which may be in square feet, square yards, or hectares, or what have you) and the price per square foot  $P_t$ . The fact that  $\gamma$  is estimated as 1 implies that the utility function takes square feet and not other area measures as an input. Setting  $\alpha = -6.7$  suggests a low substitutability between durable and non-durable consumption. If  $\alpha = 1$  then durable and non-durable goods would be perfect substitutes and no adjustment in the level of durable goods would be needed.<sup>12</sup> CES utility nests Cobb-Douglas as a special case for the limit as  $\alpha \rightarrow 0$ . Flavin and Nakagawa (2008) strongly reject ( $p < .01$ ) that alpha is zero. Although Cobb-Douglas utility functions are a common choice in two good settings, this suggests that Cobb-Douglas is an inappropriate simplification here that significantly overestimates the level of substitutability of housing and non-housing consumption.

The simulation uses friction and asset return dynamics from several empirical sources.

$$P_{2006} = 113 \quad R_f = 1.042 \quad \lambda = .05$$

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<sup>11</sup>See for example Discounting and Intergenerational Equity (1999) by Portney and Weyant for justifications of using everything between a discount rate of 0 and stock market returns. Trachtenberg (2011) argues that the proper discount rate for a social planner is negative because of rising willingness to pay for safety, environmental protection, and medical care.

<sup>12</sup>Unless wealth falls so much that the desired non-housing consumption is negative. Since consumption has to be positive, in this case adjustment would be necessary even of housing and non-housing consumption were perfect substitutes.

Real stock market return data calculated from Bureau of Labor Statistics' Consumer Price Index - All Urban Consumers series and Fama-French U.S. Research Returns Data (1950-2010). While home quality and land prices (with associated amenities) vary a great deal, US Census Bureau data estimates the cost of new construction at the peak of the housing boom at \$113 a square foot.<sup>13</sup> An annual home price return series is calculated from the CS10. These data motivate the return distributions in tables 1.1 and 1.2. While transaction costs associated with selling a home vary significantly (from very low for retirees selling a home "for sale by owner" to Realtor.com for a local move to very high for a busy professional selling a problem home and moving across country), the most accurate estimate appears by Haurin and Gill (2002) of 5%, motivating the value of  $\lambda$  used in this paper. This may be a low estimate because it is calculated from military families who plausibly have lower than typical moving costs. Ommeren and Leuvensteijn (2005) estimate the equivalent of  $\lambda$  as 6% - 22% in several European countries. Sensitivity tests confirm that a larger value of  $\lambda$  dampens the response of consumption to wealth shocks. This is consistent with Grossman and Laroque (1990a) which finds higher housing transaction costs reduces the fraction of wealth held in risky assets.

## 1.5 Simulation Results

In the overview of the model in Section 1.2, the model was transformed into various intensive variables (e.g.,  $c_t = \frac{C_t}{H_t}$ ) to eliminate a state variable from the optimization process. This transformed problem is the one solved computationally. Once solved, the policy functions can be rewritten in more intuitive quantities. Now policies are normalized to be fraction of total wealth  $W_t$  (e.g.,  $\frac{C_t}{W_t} = \frac{c_t}{y_t + P_t \cdot \lambda}$ ). These new policy functions describe what fraction of wealth goes to what purpose at each level of

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<sup>13</sup>According to US Census data (using reports 2011 reports Median and Average Sales Price of Houses Sold by Region and Median and Average Square Feet of Floor Area in New Single-Family Houses Completed by Location), the median new home price at the peak of boom (2007 Q2 in their data) was \$257,400 and a median size of 2,277 square feet which implies a construction cost of approximately \$113 a square foot inclusive of land costs. New homes are often built with higher ceilings, on bigger lots, to higher standards of finish, and in more expensive areas, so this may be a significant overstatement of the square footage price of existing existing homes. However, if newer homes provide more services for a given square footage, they may still be effectively the same price for units of service flow.



$y_t$ . There is also a renormalization of  $y_t$  so that policies are instead a function of  $\frac{W_t}{H_{t-1}}$ . Where  $y_t$  is a measure of wealth net of transaction costs relative to the quantity of housing,  $\frac{W_t}{H_{t-1}}$  is a measure of pre-adjustment cost wealth relative to the quantity of housing. While  $y_t$  is easier to manipulate analytically it can be confusing when comparing policy functions across different values of  $P_t$  and  $\lambda$ . Two households with the same  $H_{t-1}$  have three ways to have different  $y_t$  (different  $W_t$ ,  $\lambda$ , or  $P_t$ ) but only one way to have a different ratio of wealth to housing (different wealth). This also simplifies comparison with figure one of Grossman and Laroque (1990b) which plots the equivalent of  $\frac{W_t}{H_{t-1}} - 1$  against  $\frac{X_t}{W_t}$ . Figures 1.2, 1.3, and 1.4 show the model's policy functions for housing, consumption, and risky assets. In an analogous frictionless model, all three of these plots would be horizontal lines with levels determined by expected returns, preferences, and  $P_t$  because expenditures are constant fractions of wealth conditional on  $P_t$ . The housing adjustment cost alters the policy functions considerably from the frictionless case. Each policy function is considered in turn.

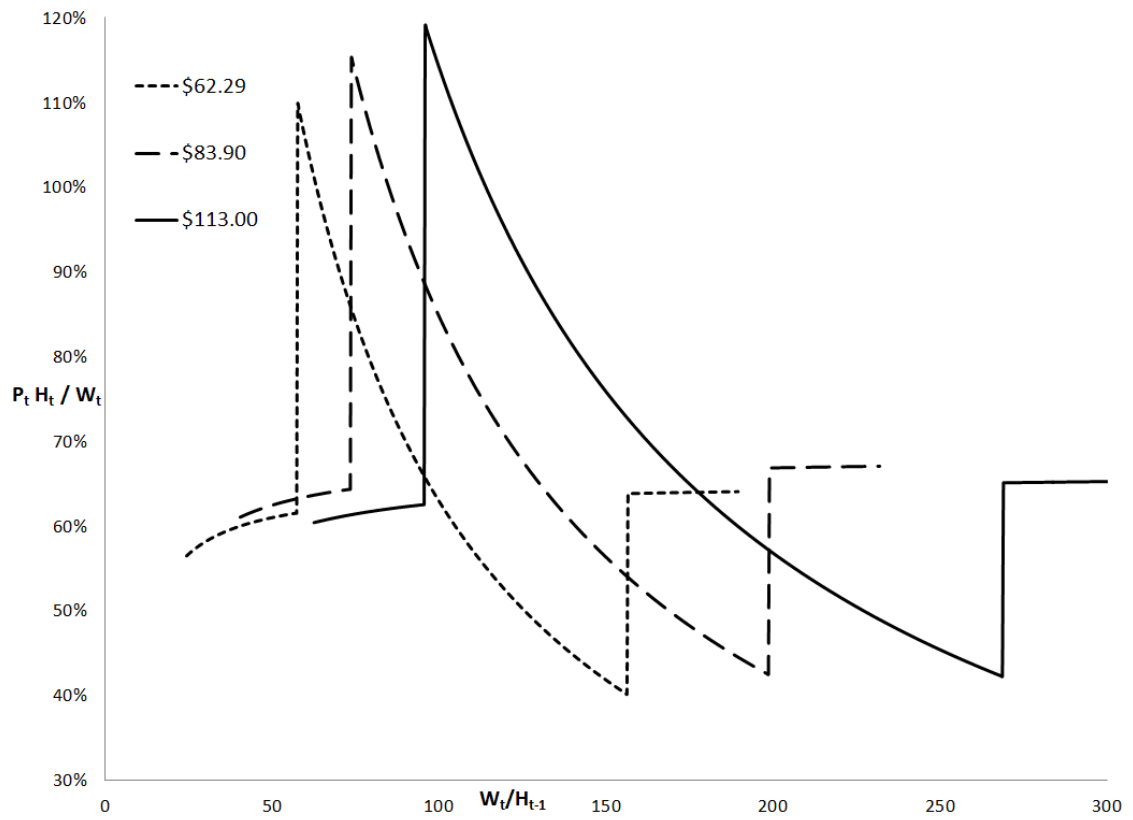
### 1.5.1 Housing Policy

Figure 1.2 shows the housing policy function for various values of  $P_t$ . Within the inaction region on housing (the S-s bounds), the share invested in housing is mechanical:

$$\frac{P_t H_t}{W_t} = \frac{P_t H_{t-1}}{W_t} = \frac{P_t}{\frac{W_t}{H_{t-1}}}$$

Holding everything else constant, doubling  $\frac{W_t}{H_{t-1}}$  halves the budget share of housing. Outside of the S-s bounds, households select a new home. Within the range of house prices studied, spending on new homes is approximately 60-65% of household wealth. The strong complementarity between durable and non-durable consumption insures that households want to consume them in fixed proportions if possible. Therefore, after adjustment the price impacts the quantity of housing but not the budget share of housing.

The price of housing influences the the S-s bounds. Notice that the S-s bounds both widen and shift to the right as house prices increase. A higher house price widens the bounds because the cost of adjustment  $\lambda \cdot H_{t-1} \cdot P_t$  is also higher. When the adjustment cost is larger households partially compensate by adjusting the policy to pay



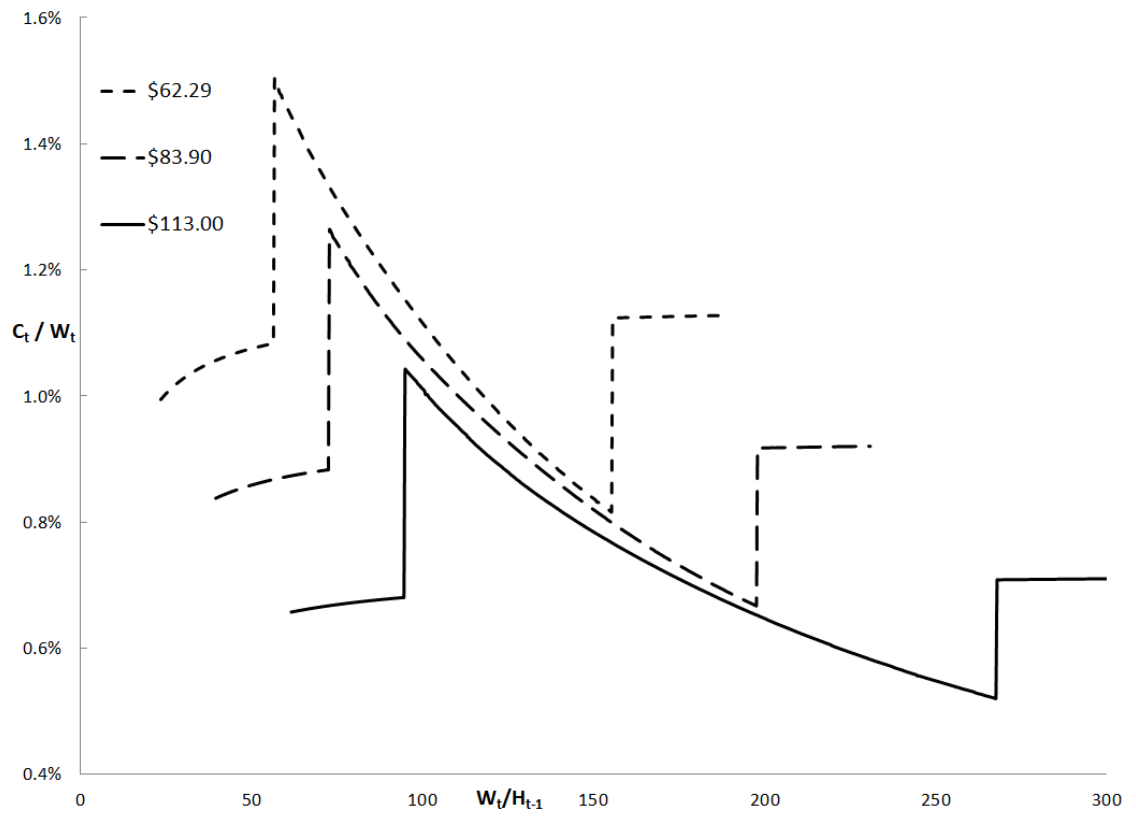
**Figure 1.2:** Housing Policy Function for Selected  $P_t$

the adjustment cost less frequently. For the intuition, consider that in the extreme, if housing were free transaction costs would be zero and all households could adjust. The rightward shift is a product of the upper S-s bound increasing more than the lower one as  $P_t$  increases. This happens because of the income effect from the pattern of adjustment. A household adjusting down is cashing out a too valuable home and using the proceeds to buy a smaller one. A higher home price means this sale raises more money. In contrast, a household adjusting up is a net buyer of housing. A higher price means they pay more for a given change in housing units. Therefore, household trading up needs a larger  $\frac{W_t}{H_{t-1}}$  before adjusting is optimal than they do when house prices are lower. This unequal income effect combined with the equal transaction costs effect moves the upper S-s more than the lower one.

## 1.5.2 Consumption Policy

Figure 1.3 shows the consumption policy function. Notice that a greater fraction of wealth is spent on non-durable consumption ( $C_t/W_t$ ) when  $\frac{W_t}{H_t}$  is relatively small. The intuition is as follows. When a household has relatively too much house for their current level of wealth they would like to cut both non-durable and durable consumption. However, the losses from paying the transaction cost outweighs the gains from adjusting durable consumption. Recall that durable and non-durable consumption are complements in the model. Under complementarity, the high level of unchanged durable consumption raises the marginal utility of non-durable consumption compared with what it would be if the household had adjusted the durable good. Therefore, the optimal share of wealth to spend on non-durable consumption is relatively higher. Conversely, if the household has relatively too little house for their current wealth then this complementarity depresses the marginal utility of non-durable consumption. This reduces the optimal share of wealth to spend on non-durable consumption.

This may seem counter-intuitive. How can a household with too much housing afford to spend more of their wealth on consumption? The answer is in two parts. First, when comparing two households (within the S-s bounds) facing the same economy and current housing  $H_{t-1}$ , the one with the higher  $\frac{W_t}{H_{t-1}}$  consumes more units of non-durable consumption ( $C_t$ ). It is only the share of wealth consumed that is higher for



**Figure 1.3:** Consumption Policy Function for Selected  $P_t$

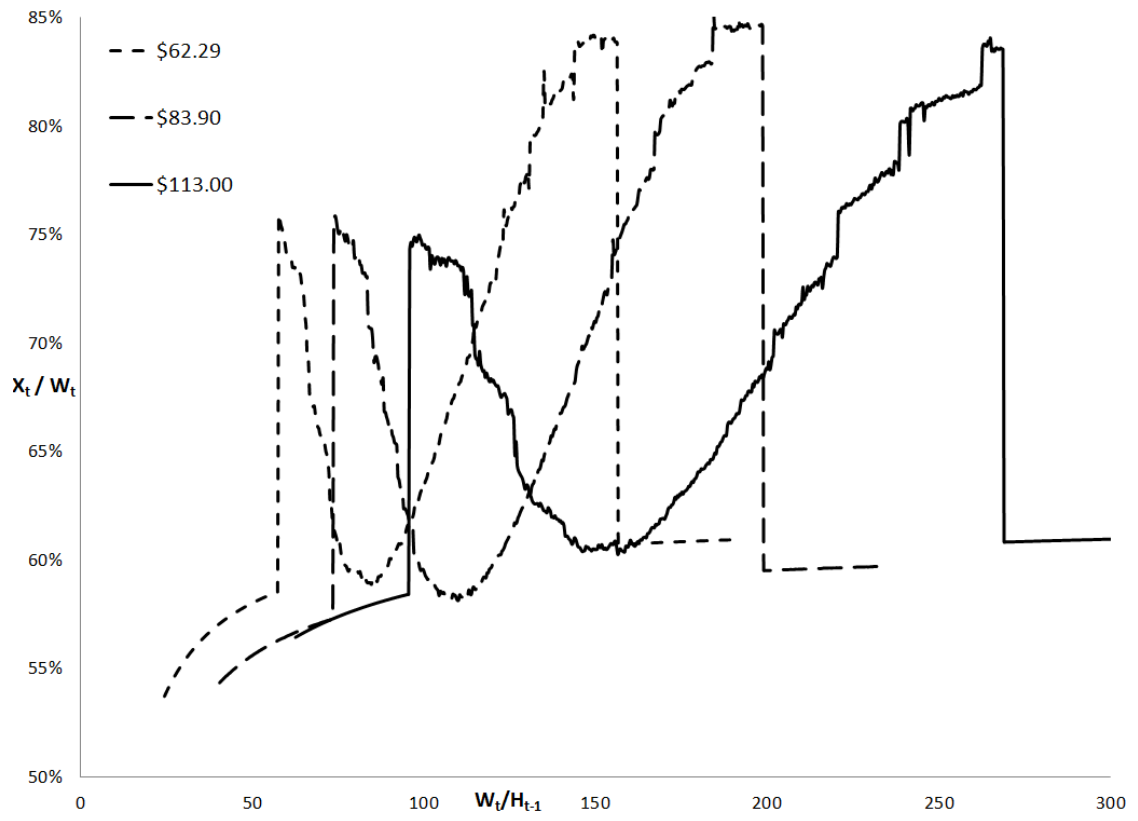
the household with the smaller  $\frac{W_t}{H_{t-1}}$ . The higher fraction of wealth consumed is not enough to compensate for the lower wealth. Second, they do not plan on being in that position forever. Eventually when they follow the optimal policy they will either exit the S-s bound and adjust their level of housing or experience enough positive wealth shocks that they move back into a region where they consume a smaller fraction of their wealth each period.

Varying the price of housing does not alter any of this basic logic. However, it does change the domain and range of the policy function. The range is governed by the transaction cost and income effects from the housing policy function discussion. The range is controlled by wealth and substitution effects. The income effect is that lower housing prices mean households can afford more of everything. The substitution effect is that lower housing prices raise the relative cost of non-durable consumption, making households purchase relatively more housing. Because of the strong complementarity of durable and non-durable consumption the wealth effect is stronger than the substitution effect and households consume a higher fraction of their wealth when house prices are lower.

### 1.5.3 Risky Asset Policy

Figure 1.4 shows the risky asset policy function. Notice the general 'U' shape of the risky asset's share of wealth with respect to  $\frac{W_t}{H_{t-1}}$ . This is caused by household risk preferences that depend on  $\frac{W_t}{H_{t-1}}$ . One way to see this in figure 1.5. In the frictionless setting, there is a constant curvature of the value function. With the frictions, the curvature of the value function depends on  $\frac{W_t}{H_{t-1}}$ . When  $\frac{W_t}{H_{t-1}}$  is near the S-s bounds there is less curvature. When  $\frac{W_t}{H_{t-1}}$  is near the return point (the value of  $\frac{W_t}{H_{t-1}}$  chosen when adjusting) there is more curvature. Those households with high curvature are more risk adverse (in an Arrow-Pratt sense) than those with low curvature.

Alternatively, consider a household near the upper S-s bound. If they chance a risky investment and it pays off they can afford to adjust their housing position. This makes them better off two ways, they can afford more non-durable consumption and the ratio of wealth to housing is also more optimal. On the other hand, if the investment does poorly then the ratio of wealth to housing falls towards the return point, becoming more



**Figure 1.4:** Risky Asset Policy Function for Selected  $P_t$

optimal. This partly offsets the effect of wealth. By improving the ratio both the good and bad outcomes are better than the straight wealth effects suggest. This lowers the required certainty equivalent and makes the household less risk averse (again in an Arrow-Pratt sense). On the other hand, consider a household at the return point. Positive and negative returns on the risky investment both move the household away from the efficient wealth to housing ratio. Now the efficiency effect is reversed, raising the certainty equivalent because good and bad outcomes are both worse than if there were only a wealth effect.

Notice that this discussion does not depend on  $P_t$ . This ensures that the portfolio holdings are the same near these points. However, because of the transaction cost and income effects these points shift right and spread apart as the price of housing increases. This widens the “U” shape of the policy function but leaves the levels at the three anchor points unchanged.

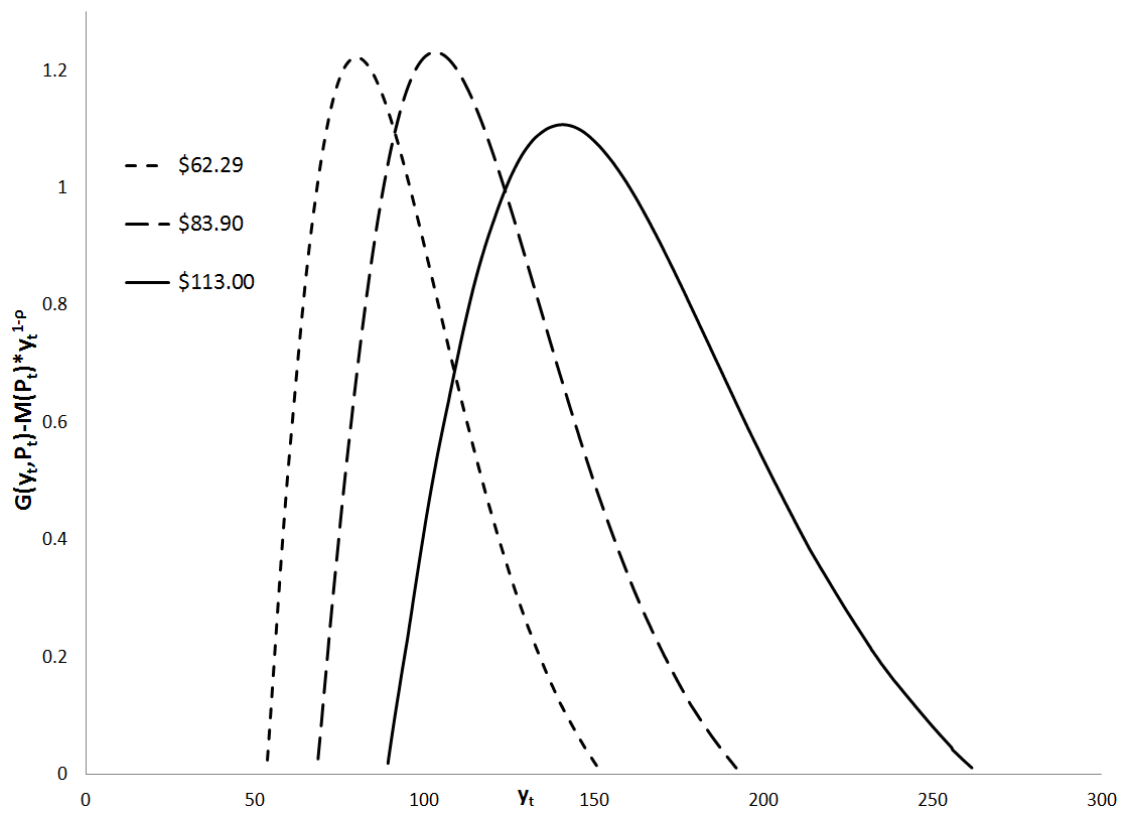
#### 1.5.4 The Value Function

These three optimal policy functions imply the household’s value function. In the frictionless case the value function takes the constant relative risk aversion form. In this model the overall level of the value function is lower because there is an inefficiency induced by not consuming the durable and non-durable consumption in optimal (under no frictions) proportions and a wealth effect that households are poorer because they have to actually pay the transaction cost. Grossman and Laroque (1990a) prove that in their model with housing and a non-convex adjustment cost (but without house price dynamics or non-durable consumption) that outside of the S-s bounds (the adjustment region) the value function takes a form  $M \cdot y_t^{1-\rho}$  (where M is a constant) and that value function has the same curvature as in the frictionless case. This result is also found in this paper’s simulations: in the adjustment region the value function takes the form  $M(P_t) \cdot y_t^{1-\rho}$  and the curvature of the value function is the same as the frictionless case and controlled by  $\rho$ . Within the S-s bounds there is a hump where the value function is greater than  $M(P_t) \cdot y_t^{1-\rho}$ . Figure 1.5 shows this hump, the difference  $G(y_t, P_t) - M(P_t) \cdot y_t^{1-\rho}$ .<sup>14</sup>

The hump occurs because adjusting housing is costly. It is optimal to adjust

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<sup>14</sup>This is analogous to G&L’s figure 2.



**Figure 1.5:** The Option Value of Delayed  $H_t$  Adjustment Depends on  $P_t$  and  $y_t$  (Selected Values of  $P_t$ )



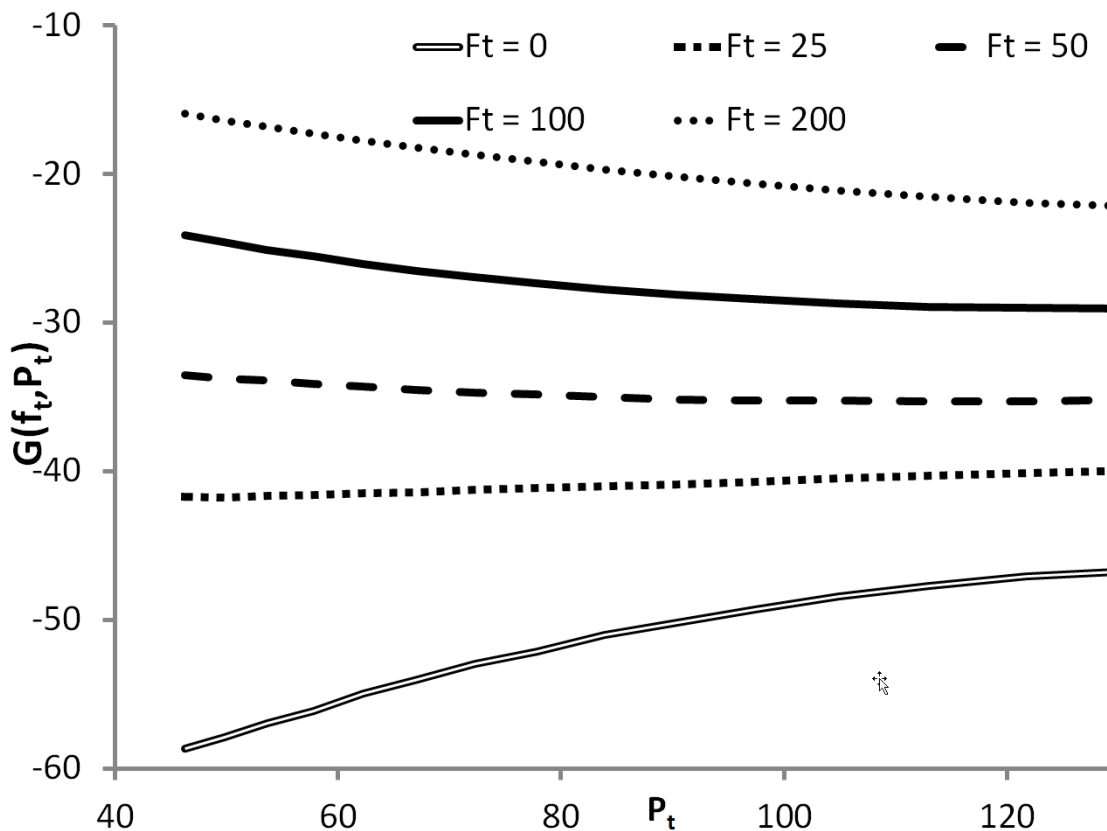
only when the wealth effect of paying the transaction cost is offset by the efficiency gains of altering the consumption bundle. However, households can choose not to adjust housing. The right but not the obligation to adjust housing is an option held by the household. The value of that option to the household (measured in utility) is the difference  $G(y_t, P_t) - M(P_t) \cdot y_t^{1-\rho}$ . This hump represents the option value of not adjusting. Outside of the S-s bounds the household is worse off not adjusting and the right to not adjust this period has no value.

The option value for a given value of  $y_t$  depends considerably on  $P_t$ . Again this is because of a wealth and efficiency effect. When the price of housing is higher so is the adjustment cost and therefore the value of not paying that cost is higher (wealth). Unfortunately for the household, when  $P_t$  is higher they expect to spend longer in their new home and farther away from the optimal ratio of housing to wealth then they would at lower prices. Overall, as home prices increase the inefficiency effect dominates and the option value declines.

### 1.5.5 Implications for the Wealth Effect of Housing Price Changes

This model predicts a differential wealth effect from housing price changes depending on household wealth not invested housing. Define this liquid wealth as  $f_t \equiv \frac{W_t - \lambda P_t H_{t-1} - P_t \cdot H_{t-1}}{H_{t-1}}$ . Figure 1.6 depicts this differential effect for five levels of liquid wealth. There are two effects present. First, when the price of housing increases households get more units of non-housing consumption for each unit of housing they give up. Second, the cost of additional housing has increased. In some households, like those where  $f_t = 0$ , the first effect dominates. They are expecting to sell their home and move into a smaller one so the price increase frees up more wealth to use on non-housing consumption. In others, like those where  $f_t = 100$ , the second effect dominates. They have much liquid wealth relative to their home size and they are expecting to sell their home soon to buy a larger one and therefore their planned upgrade has become more expensive. For households with  $f_t = 25$  these forces are approximately balanced and price changes leave household welfare mostly unchanged.

The above analysis is surprising given the positive marginal propensity to consume out of housing wealth ( $MPC_H$ ) found in the literature. Indeed, the  $MPC_H$  is

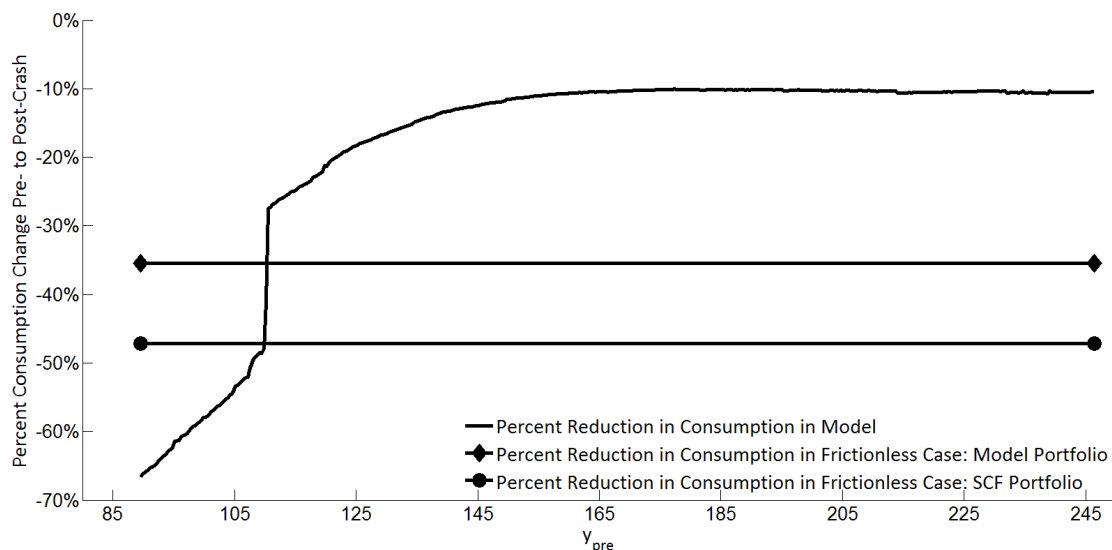


**Figure 1.6:** Home Price Increases Often Make the Household Worse Off Holding Fixed Housing and Financial Assets

generally believe to be larger than the marginal propensity to consume out of financial wealth ( $MPC_F$ ). At first it is difficult to reconcile these findings. However, if households are simply substituting, reducing their planned consumption of housing and increasing their relative consumption of non-housing goods, what appears to be a high  $MPC_H$  may well be simply the abrupt change in planned consumption from the change in the relative prices, combined with the effects of a transaction cost that delays full adjustment.

### 1.5.6 Implications for Consumption Dynamics

To study the model's replication of empirical macroeconomic consumption dynamics, it is useful to study the model's predicted consumption changes to historical changes in home prices and stock market returns. Figures 1.7 and 1.8 highlights the

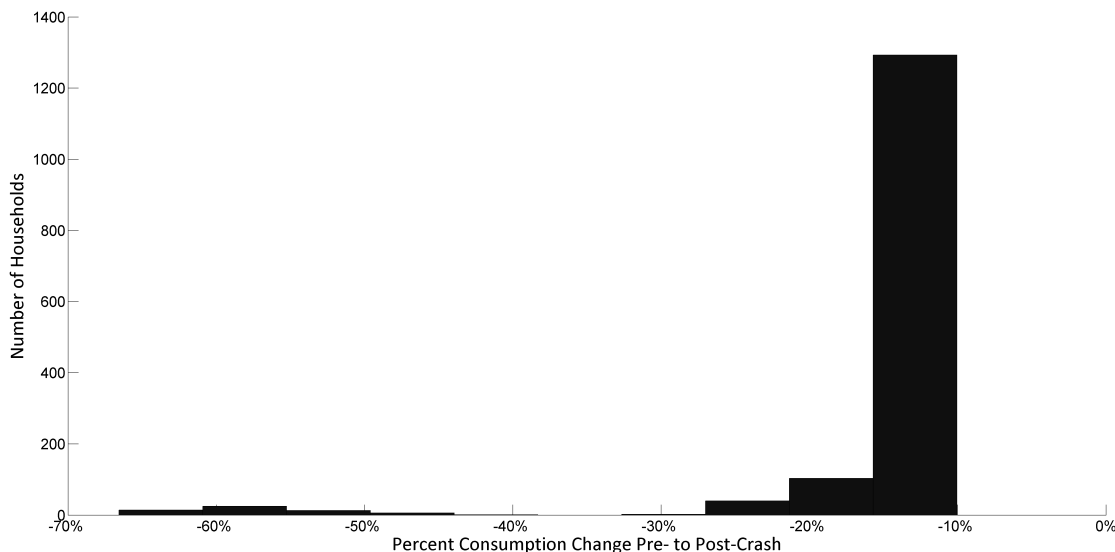


**Figure 1.7:** Changes in consumption depend on  $y_{pre}$

basic model results. Figure 1.7 shows agents' consumption and wealth responses from 2006 to 2008 when the US stock market fell 39% and national home prices fell 31%. Relatively house rich agents ( $y_t$  large pre-crash) lowered their non-durable consumption by approximately 10%. Progressively more house poor (relatively too much housing) agents decreased their consumption by larger amounts but less than 20%. A subset of agents (those with smaller  $y_t$ ) move into smaller homes and have vastly lower consumption with declines of 45% or more. The other line in figure 1.7 is the changes in wealth for each value of pre-crash  $y_t$ . In a frictionless model (like Lucas (1978)) where agents make the same investment decisions consumption is a constant fraction of wealth and so this would also be the consumption response. Overall, this model delivers much smaller (and more realistic) consumption adjustment for most agents. Some agents adjust more in the model than they would in a frictionless setting. However, real households forced to downsize due to diminished wealth and job prospects are likely to make atypically large non-durable consumption adjustments. Therefore, general response shape is realistic, even if the precise magnitudes are perhaps unrealistically large.

Figure 1.8 is a histogram of household's percent consumption changes. It highlights that the vast majority of consumption changes are far less than the average change in wealth.

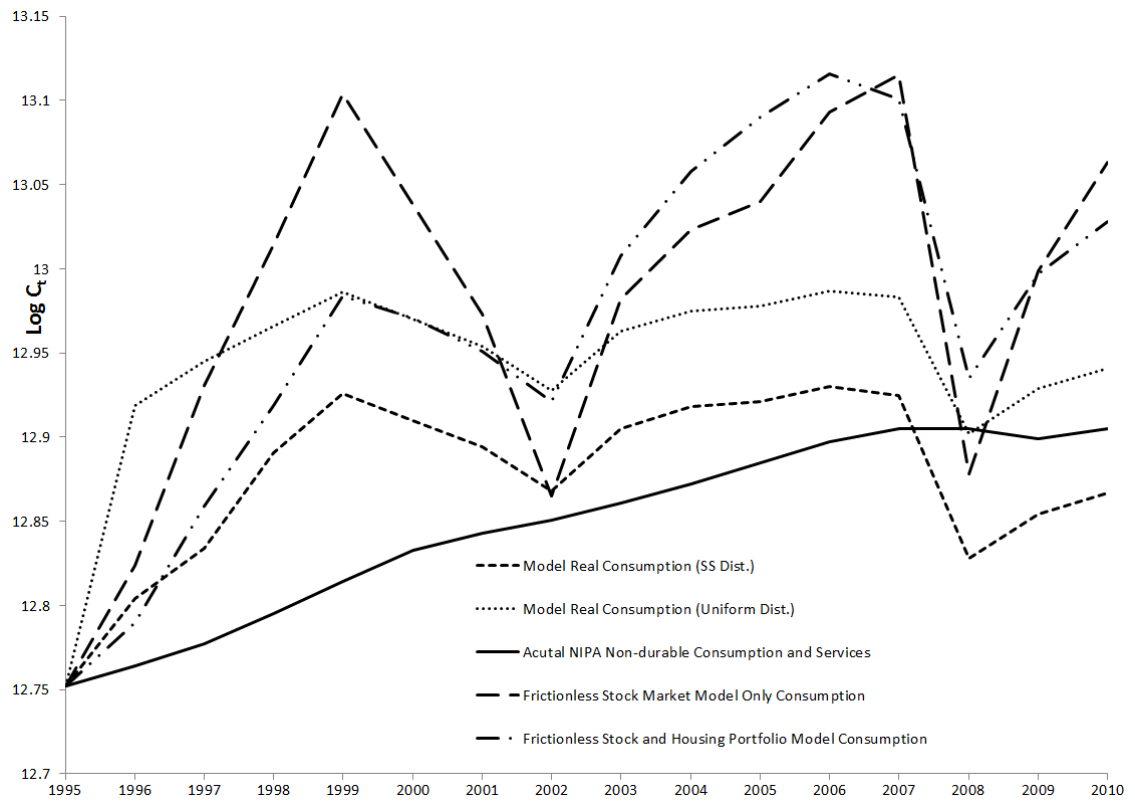
Figures 1.9 and 1.10 respectively examine the path of consumption predicted by



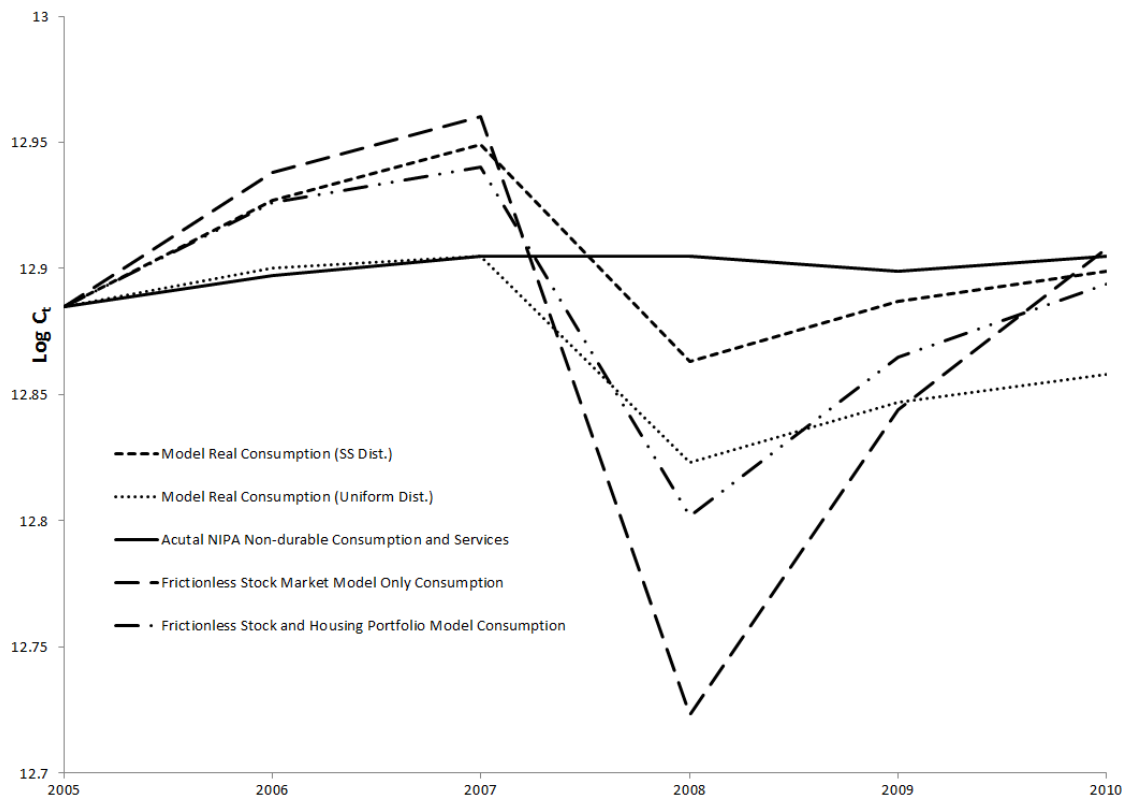
**Figure 1.8:** Most households change consumption much less than their change in wealth

the model and over the historical asset returns in the years 1995-2010 and 2005-2010. They also show the response of two alternative frictionless models. The first, “Frictionless Stock Market Model” assumes that all household wealth is held in the market portfolio of stocks. The second, “Frictionless Stock And Housing Portfolio Model Consumption” assumes that households hold their assets in a mixture of housing (45%) and risky assets (55%) consistent with portfolio composition in the 2004 Survey of Consumer Finance. Again, since in both models consumption can be costlessly adjusted, percent changes in wealth are percent changes in consumption.

Within the model, agent consumption changes depend on  $y_t$ . Therefore, this requires some assumption about the initial distributions of  $y_t$  in the economy before the the shocks are introduced. Two methods are employed. First, the joint distribution of of  $P_t$  and risky asset returns implies a steady state distribution of  $y_t|P_t$ . Alternatively, a uniform distribution of  $y_t$  values between the S-s bounds is used. As a further refinement these distributions can start at different times. Figure 1.9 starts the simulation in 1987. However, since NIPA data on true non-durable and service consumption starts in 1995, only those results starting in 1995 are shown. Figure 1.4 starts the simulation just before the crash in 2005. Tables 1.3 and 1.4 provide the data used to create these plots, as well as the sum of squared error from true consumption process reported in the NIPA.



**Figure 1.9:** Aggregate Consumption Plots: Starting Distribution of  $y_t$  in 1987



**Figure 1.10:** Aggregate Consumption Plots: Starting Distribution of  $y_t$  in 2005

**Table 1.3:** Goodness of Fit: Starting Distribution of  $y_t$  in 1987\*

Year	Model Real Consumption (SS dist)	Model Real Consumption (Uniform dist)	Actual NIPA Non-durable Consumption and Services	Frictionless Stock Market Model Only Consumption	Frictionless Stock And Housing Portfolio Model Consumption
1995**	12.752	12.752	12.752	12.752	12.752
1996	12.806	12.919	12.764	12.824	12.79
1997	12.836	12.945	12.777	12.931	12.859
1998	12.896	12.966	12.795	13.014	12.919
1999	12.932	12.986	12.814	13.104	12.984
2000	12.916	12.97	12.833	13.038	12.971
2001	12.9	12.954	12.843	12.973	12.951
2002	12.873	12.928	12.851	12.865	12.921
2003	12.91	12.963	12.861	12.982	13.008
2004	12.924	12.975	12.872	13.023	13.058
2005	12.927	12.978	12.885	13.04	13.09
2006	12.935	12.987	12.897	13.093	13.116
2007	12.931	12.983	12.905	13.115	13.101
2008	12.833	12.902	12.905	12.878	12.935
2009	12.859	12.929	12.899	12.999	12.997
2010	12.872	12.941	12.905	13.063	13.028
SSE	188.4	358.2	.	1379.9	525.8

\* - Case-Shiller data starts in 1987

\*\* - NIPA non-durable consumption data starts in 1995

**Table 1.4:** Goodness of Fit: Starting Distribution of  $y_t$  in 2005

Year	Model Real Consumption (SS dist)	Model Real Consumption (Uniform dist)	Actual NIPA Non-durable Consumption and Services	Frictionless Stock Market Model Only Consumption	Frictionless Stock And Housing Portfolio Model Consumption
2005	12.885	12.885	12.885	12.885	12.885
2006	12.927	12.9	12.897	12.938	12.926
2007	12.948	12.905	12.905	12.96	12.94
2008	12.862	12.823	12.905	12.723	12.802
2009	12.886	12.847	12.899	12.844	12.865
2010	12.898	12.858	12.905	12.908	12.894
SSE	94.7	77.9	.	774.7	252.2

Both  $y_t$  distributions outperform the two frictionless models in terms of tracking error. When starting in 1987, the steady state distribution has much smaller tracking error. When starting in 2005, the uniform distribution has slightly lower tracking. In both simulations, both calibration roughly have a third of the error of the frictionless models. The model predictions are particularly good in period of the Great Recession, with much smaller consumption responses.

In practice, many households walk away from mortgage obligations rather than suffer too much non-durable consumption reduction. Therefore model prediction of exits on the low end should be a proxy for delinquent mortgages, perhaps with some delay. There are health and labor force reasons why people get into delinquency, so for many years national mortgage delinquencies were low and steady in America. The model predicts that depending on starting period and distribution of  $y_t$  that between 2% and 10% of households would hit the lower S-s bound and adjust into a smaller home in 2008 as a result of the great recession after more than a decade of no households hitting this lower bound. This is roughly contemporaneous with the massive increase in mortgage delinquencies from historical levels.

It is possible that another omitted asset, human capital, could instead deliver these results. Appendix B provides a back of the envelope estimate of how large these human capital effects might be. These human capital effects alone are not large enough to deliver realistic consumption dynamics. However, when combined with the housing model, human capital gives even more accurate replication of aggregate consumption dynamics.

## 1.6 Conclusion

Models without non-convex transaction costs on adjusting housing holdings are more tractable. Therefore, we would prefer them if they gave the same quantitative and qualitative predictions. However, these frictions deliver substantially different consumption and investment policy functions. These functions have implications on the co-movement of aggregate consumption dynamics and asset prices that look much more like the actual co-movement of these series than that of models without this key friction.



The model also makes household level predictions. Households are predicted to smoothly reduce consumption in response to small wealth shocks and discontinuously to large wealth shocks that induce them to adjust their housing. They are also predicted to make infrequent large adjustment to the house holdings. These predictions are consistent with the microeconomic evidence. Households that have recently adjusted their housing are predicted to hold less of the risky asset while those considering moving for financial reasons ( $y_t$  near the S-s bounds) should be more risk tolerant. This could be why Banks et al. (2002) and Flavin and Yamashita (2002) find that young households who on average have moved more recently hold less of their wealth in stocks.

There are other omitted assets on the household balance sheet. Particularly, human capital (or alternatively labor wealth) is not treated and it is large, illiquid, difficult to borrow against, and considerably less variable (especially in aggregate) than housing or stock markets. Households also have access to bankruptcy and social insurance. There are other macroeconomic dynamics buffeting the household beyond asset returns. All should have an affect on household consumption and investment and therefore it would be a surprise if adding housing alone would perfectly match aggregate dynamics. Though the resulting dynamics are still too volatile relative to observed non-durable consumption, this paper shows that a serious treatment of housing goes far towards generating realistic household behavior. A natural extension to this work is adding labor income or human capital to the model. The back of the envelope calculations in Appendix B suggest that between housing and human capital, most of the consumption dynamics can be captured.

# Chapter 2

## Do Information Releases Diminish Equity Bid-Offer Spreads?

### 2.1 Introduction

#### 2.1.1 Understanding the bid-offer spread

A popular measure of the transaction costs of trading and the liquidity of a security is its bid-offer (also called the bid-ask) spread.<sup>1</sup> The bid-offer spread measures the difference between the price for which you can buy an asset (the ask or offer) and the price for which you can sell it (the bid). In normal functioning markets, the offer is larger than the bid and therefore the bid-offer spread is positive.<sup>2</sup> Bid-offer spreads are quoted differently depending on if the market trades on price or yield. This paper examines the behavior of the bid-offer spreads of the equity shares of publicly traded US corporations. Their spreads, like their prices, are quoted in dollars and cents.<sup>3</sup>

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<sup>1</sup>See for example Bagehot (1971); Glosten and Milgrom (1985); Glosten (1987); Huang and Stoll (1997); Admati and Pfleiderer (1988); George et al. (1991). This paper focuses on the liquidity consequences of the bid-offer spread, but the transaction costs consequences are also important. The bid-offer spread influences asset returns by increasing buying costs and lowering selling prices. Consider the following example. Stock ABC trades with a spread of 2%, a mid price of \$100 a share, and no dividends. Buying one share costs you \$101. A year later the mid is \$110 and spreads are still 2%. You sell your share for \$108.9 for  $\approx 7.82\%$  net return instead of 10% gross return.

<sup>2</sup>Under the unusual circumstances that the offer is smaller than the bid. Such a market is called crossed and attentive market participants have an arbitrage opportunity.

<sup>3</sup>Products that trade on their yield and not price like bonds and many swaps typically have spreads quoted in hundredths of a percent called basis points

As a measure of the cost of investment reversibility (the cost of opening and closing a position), small bid-offer spreads are usually associated with liquid markets. The spread is also a proxy for other senses of liquidity like the expected time to sale without diminution explored by Lippman and McCall (1986) or the reliability of an asset's value by Tobin (1958) and Hicks (1962).

While clearly a critical aspect of asset liquidity, bid-offer spreads are not the entire cost of trading. Most stock trades also involve brokerage fees. If shares are held in taxable accounts then capital gains and dividend taxes will also drive a wedge between the value of the asset to the holder and what price the investor can trade it at even with perfect information and the absence of other costs. Nevertheless, competition in the brokerage business and the large percentage of investment dollars held by tax-free entities like pensions, insurers, charity endowments, and mutual funds in tax-free accounts keep these other costs low, making paper's abstraction from these other costs an acceptable approximation and one used extensively in this literature.

Bid-offer spread do not fully describe an asset's liquidity. Investors may value anonymity and speed in trade over paying the lowest possible transaction costs. These factors are not reflected in the bid-offer spread but are features asset liquidity. The spread is a popular measure because summarizes with a single number the cost of reversing a stock position, yet still is indicative of the more complex true liquidity and transaction costs of trading an asset. Despite not being a perfect measure, its connection to the cost of trade, ready measurability and wide regard as a useful estimate of overall asset liquidity has made it the primary object of study in understanding asset liquidity.

There are at least four components of the bid-offer spread. They are the order processing, trade facilitation, market maker rents, and the adverse selection costs of trade. Demsetz (1968) identified the order-processing and trade facilitation (what he calls market making costs) while Glosten and Milgrom (1985) and Glosten (1987) introduces the adverse selection component.<sup>4</sup> It is common in the literature to assume that market makers operate in a competitive market and so earn no rents.

The order processing costs are the costs of maintaining an exchange (rent, equipment, and staff), recording the trades, handling the billing, and delivering the shares.

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<sup>4</sup>However, the idea of adverse selection in insurance markets is well established and presumably practitioners have long integrated this component into their quotes.

Most of these costs are fixed costs in advanced computerized order processing systems and salaried staff. Market makers must make costly long term capital allocation decisions that determine their capacity, but then the marginal order processing costs are low.

The second component is the the trade facilitation costs of market makers from counterparty search and inventory. Market makers are firms that ensure an orderly movement of prices and a minimal level of liquidity in the shares they trade. They do so by either trading directly with buyers and sellers out of their accounts or by finding others who would like to trade. Because the market maker must hold securities (to offer them for sale) and have credit or free cash (to purchase more) they must raise and tie up a significant amount of capital in an un-diversified investment. To finance this capital, bear this idiosyncratic risk, and tolerate the remaining market risk in the face of their risk aversion they must be compensated. The ability to conduct counterparty searches on behalf clients requires a costly network of contacts and a staff to work those contacts. To fund these expenses, market makers generate income from the bid-offer spread in the stocks they trade. The capital required to perform this role is a function asset price volatility and co-variability, the costs of trade, and the expected search time to find other participants to take the other side of trades. High transaction costs, idiosyncratic risk, and long searches drive this component of the spread larger.

The third component of the bid-offer spread is the rents from market power of market makers. Most of the spread decomposition literature assumes that such profits are exogenous and fixed like Glosten (1987) or zero like Bagehot (1971). Market making appears competitive. Loughran and Schultz (2005) use contemporaneous data to find an average of about 8 large market makers on a typical NASDAQ listed firm. NYSE listed firms have only one market maker, but face on exchange competition from specialist, floor traders, and limit-order submitter and off-market competition from electronic communication networks, dark-pools, and block trading desks. Barclay (1997) finds evidence in some firms that NASDAQ market makers co-ordinate on avoiding odd eighths trading to increase spread size but Benston (2007) provides an alternative explanation without collusion. That market making remains an activity with many participants under significant regulatory scrutiny and with low long term barriers to entry suggests that

spreads are above the marginal cost of trade but not far above average cost. Kreps and Scheinkman (1983) set up a two stage game where firms determine capacity and then compete on price. As long as the capacity costs and marginal costs of trade are convex this allows the sum of the two cost functions to determine the market price and therefore long run average costs to be the competitive price. This is one theoretical justification for the assumption employed in this paper of modeling part of the order processing and trade facilitation costs components of the bid-offer spread as declining approximately with the inverse of volume and no rents for market makers.

The fourth component of the bid-offer spread is compensation for adverse selection. Measuring changes in this component is the focus of this paper. Market makers must contend with counterparties that have material private information. Yet these informed traders are indistinguishable from noise traders who have no additional information on an asset's true value. It would not be profit maximizing for market makers to allow informed traders to make large trading profits using their information and only after to move securities prices. Instead, market makers anticipate how that information would move the market and they increase the spreads so that some of that price movement is already built into the spread. They still lose some money to the informed traders but they make it back in larger profits from the noise traders. The size of this component varies with the relative number of noise and informed traders, their holdings and purchasing power, and the value of their private information. Glosten and Milgrom (1985) show that in a risk neutral and competitive setting, where market makers knew the distribution of informed and noise trading, market makers would set the adverse selection fee such that they made zero profits in expectation. The entire fee collected from the adverse selection spread would be captured by the informed traders.

These components vary widely in size. According to estimates by Huang and Stoll (1997), order processing costs are 61.7% of observed spreads, inventory costs are 28.7%, and adverse selection costs are 9.6% of the observed spreads. George, Kaul and Nimalendran (1991) (GKN) attribute 8-13% of the spread to adverse selection in a model where inventory costs are assumed to be zero and so order processing costs are between 87% and 92% of the spread. (Madhavan et al., 1997) measure an adverse

selection component of about 43%.<sup>5</sup> Gibson et al. (2002) estimate that 33.2% of the spread is adverse selection and inventory costs with the remainder in order processing costs.

However, all these models are calculated from inventory accumulation models like that of Ho and Stoll (1981) and Stoll (1978). They rely upon stylized identifying assumptions. Huang and Stoll (1997) assume a specific form for the serial correlation of trade flow as does GKN which also assumes that inventory costs are zero. Given short waiting times between trades, low cost search for counterparties, and small average trade sizes, inventory accumulation may be the wrong model for understanding how market makers set their spreads. Beyond the significant variation in estimates of the adverse selection spread, there is other evidence that they are not properly specified. Neal and Wheatley (1998) show that these methods generate a large adverse selection spread (an average of 19%) on closed end mutual funds. However, by virtue of a clear liquidation value, trading in these securities should run much risk of adverse selection. Further evidence of the problems with this identification strategy comes from Clarke and Shastri (2000). They show that depending on which of these methods you use, between 14% and 60% of the time these methods result in an adverse selection component that is larger than 0% or greater than 100% which defies our intuition that all components of the spread should be weakly positive and therefore the adverse selection should always be weakly between 0% and 100% of total spreads. However, Copeland and Galai (1983) provides theoretical justification for the rough consequences of information motivated selling, even if the the precise magnitude of the effect is uncertain.

Huang and Stoll (1997) used very large American publicly traded companies to derive their estimates. GKN used a larger range of firm sizes, and find no relation between firm size and the proportion of the adverse selection component of the spread. However, their data is quite old, spanning from 1963-1985. They find average spreads of about 1.4% of share prices when looking at larger firms. This paper contains much more heterogeneity in firm size and uses more recent data. Within the larger Russell 3000 firms from 2005 to 2006, it finds average spreads of about 0.6% of share prices. Table 2.1 shows that there is considerable variation in the magnitude of spreads conditional

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<sup>5</sup>At particular times during the day they find as much as 55% of the spread is attributable to adverse selection

**Table 2.1:** Average Spread Size by Firm Size within Russell 3000

Percentile	Average Size	Average Spread
[.9,.1]	\$18,409,439,015	0.40%
[.8,.9)	\$5,187,898,786	0.48%
[.7,.8)	\$2,796,747,979	0.53%
[.6,.7)	\$1,651,553,241	0.55%
[.5,.6)	\$1,106,354,053	0.58%
[.4,.5)	\$768,588,560	0.63%
[.3,.4)	\$554,873,187	0.66%
[.2,.3)	\$387,332,090	0.78%
[.1,.2)	\$279,007,401	1.01%
[0,.1)	\$179,500,140	1.51%

Average daily spreads for Russell 3000 firms on select days in 2005 and 2005 using quote data from NYSE TAQ and size data from data from Size data from The Center for Research in Security Prices.

on firm size. Figure 2.1 shows that spreads vary considerably over time at even when controlling for size.

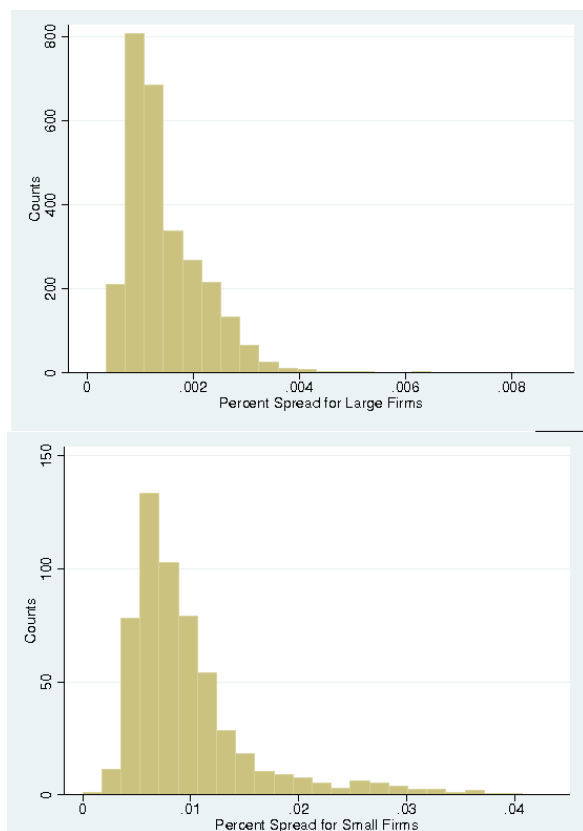
These spread estimates suggest large and likely unrealistic value of insider information. Bettis et al. (2000) established that corporate insiders trade between .21% and .66% of total share volume . This, along with the facts established so far provide a sense of the returns ( $r_{insider}$ ) made by insiders from insider trading.

$$\begin{aligned}
 r_{insider} &= \frac{\text{Insider trade profits}}{\text{Insider trade volume}} \\
 &= \frac{\text{Volume}_{\text{shares,total}} \cdot \text{Spread}_{\text{adverse}}}{\text{Volume}_{\text{shares,insider}}} \cdot \frac{\text{Spread}_{\text{total}}}{\text{Spread}_{\text{total}}} \\
 &= \text{Spread}_{\text{total}} \cdot \frac{\frac{\text{Spread}_{\text{adverse}}}{\text{Spread}_{\text{total}}}}{\frac{\text{Volume}_{\text{shares,total}}}{\text{Volume}_{\text{shares,insider}}}}
 \end{aligned}$$

Using the most conservative estimates from above:

$$r_{insider}^{GKN,1963-1985} = 0.014 \cdot \frac{0.08}{0.0066} \approx 17\%$$

$$r_{insider}^{R3000,2005-2006} = 0.006 \cdot \frac{0.08}{0.0066} \approx 7.3\%$$



**Figure 2.1:** Distribution of Spreads over the Calendar Year

Both histograms display the distribution of average daily bid-offer spreads. The first is for large firms, the second for small ones. The large companies are the 10 largest members of the Russell 3000 with December FYE in 2005 tracked from the start of June 2005 to the end of June 2006.



While the volume of trade by corporate insiders is an imperfect proxy for the trade volume of the universe of those with inside information, given the sorts of money that insiders command, it may be an acceptable proxy. If this estimate is correct, then insiders are on average making enormous profits from their inside information.<sup>6</sup> It strains credulity to believe that insiders have such valuable information on a typical day. After all, this is the average value of the adverse selection component. One way to test if the older estimates are reasonable is to see what they look like on atypical days. That is, examine days when insiders are known to have valuable information and compare them with nearby days when insiders no longer have such a large information advantage.

The above analysis requires that changes in share prices reflect changes in or at least beliefs about firm fundamentals. It could be that some process also drives prices and yet has nothing to do with the firm's economic fundamentals. The adverse selection component would then encompass both the risks of those with superior knowledge of the firm's fundamentals (fundamental adverse selectors) as well where the prices were headed because of other reasons (market sentiment adverse selectors). At first glance the market sentiment adverse selectors could be brokers front running their clients or might be the high frequency traders using algorithms to predict order flow. However, these models assume that the return process ( $\log(P_t/P_{t-1})$ ) is uncorrelated with future noise transactions. If that sort of noise prediction were happening the assumptions underlying the identification of the decomposition models above would not hold. Such predictive behavior may well be happening, but such a criticism would extend beyond this paper into the rest of this literature.

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<sup>6</sup>Subject to the caveat that the holding period of such an excess return is ambiguous. Whatever that holding period is, the model's structural form implies that such insider knowledge of the true value of shares have this value on an average day. However, considering the case of employee insiders, a short holding period makes more sense. Employees rarely purchase stock (they are typically awarded it as a form of compensation) and so their primary mechanism for trading on private information is in selling that stock. Their information is typically company performance information that will be released in at most three months at which point it will be reflected in the stock price. This suggests a daily excess return of greater than .5%. That's a lower bound. If, as this estimation strategy suggests, spreads are constant, for periods nearer to releases of information this is a much higher daily excess return.

### 2.1.2 Information Distance

This paper defines the information distance as the difference in information held by anyone with valuable private information about a share's true value (insiders) or return process and market makers (outsiders). The inventory accumulation papers discussed above treat the information distance as constant by modeling this quantity with a time-invariant parameter in their estimations. This is a simplifying assumption, but there are many reasons why the information distance varies over time. A simple example of an information distance reduction is when a firm deliberately releases inside information through a press release. Whatever had been known to insiders is now common knowledge to investors.

When the information distance decreases there is less information available to insiders with which to trade at expense of market makers. Therefore, if market makers are operating in a competitive market this reduction in information distance will translate into a smaller adverse selection component. All other things equal, it also causes the spread to shrink. Comparing the period before the release with the period after should show a decrease in the adverse selection component of the bid-offer spread. As insiders like firm management build up and release inside information, the market makers should make the adverse selection component rise and fall.<sup>7</sup> Given this, at best the papers above measure the average value of this quantity when they treat this component as fixed.

Information distance is a latent variable. This paper uses several proxies for reductions in the information distance. They share a common thread of being substantive, high profile, and widely available releases of information with known dates. Though it is impossible to perfectly measure the decrease in information distance, the occurrence of these events are acceptable proxies for its unobserved reduction. This, combined with a first difference estimation strategy and proper controls, should provide an estimate of the causal relationship between information distance and the spread. The proxies for changes in information distance are Securities and Exchange Commission (SEC) filings,

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<sup>7</sup>It is possible that other spread components are negatively correlated with the adverse selection component and so total spreads that move much less. However, given low and generally fixed order processing costs and since volumes tend to increase on release dates, this seems unlikely. In principle, this is testable. Repeat an analysis like GKN day by day and see how estimates of the spread components move together over time.

the announcement (and magnitude) of earnings surprises, and conference calls between stock analysts and firm management.

The first proxy for information distance reduction is the release of SEC filings. The most important of these documents are the 10Q (quarterly financials) and 10K (annual financials), 8K (disclosing important events between 10Q filings), 14A (the proxy statement), and the 4 (insider stock transactions), but there are many others. See Appendix C for a categorization of SEC filings with definitions and importance. For all companies these filings provide critical information to outsiders about the operations of the firm and its financial well being. However, among the large public companies that are widely studied, these SEC documents reveal relatively less information.

This change in information distance should vary by company size because large companies receive detailed attention. They have many employees, customers, vendors. Equity researchers, reporters, and the public are all relatively more interested in the firm's affairs than those of smaller firms. With all these eyes looking at the firm and mouths discussing it, the amount of material private information will generally be small. On the other hand, small companies languish in relative obscurity, covered infrequently and by fewer equity researchers. They also receive less press attention, and have fewer and less diverse vendors and customers.

For those firms that garner less attention, these SEC filings provide outside investors with critical insight into their ongoing operations. Because insiders have relatively more information, all other things equal an information release by a small firm should reduce more of the information distance than the a release by a large firm. As such, the adverse selection portion of the bid-offer spread should decline relatively more for smaller firms than for bigger ones after the release of these filings.

The second proxy for information distance reduction is earnings release conference calls with investors. These calls allow institutional investors and equity research groups to ask questions about financial statements and firm operations and outlook. This measure should also be more illuminating for small firms than larger ones. The larger firms have more opportunities to discuss corporate affairs with investors, the press, and financial intermediaries. Conference call dates too should show declines in the adverse selection component of the bid-offer spread because these calls provide an opportunity

to reduce uncertainty about a firm's real value.

The third proxy for a reduction in information distance is the timing of the release of corporate earnings and earnings surprises. Earnings surprises occur when the estimates of corporate earnings by stock analysts that cover a company are different from the actual earnings that the company releases. The average of their estimates is called the consensus estimate. To the extent that there is greater uncertainty about a firm's earnings, it is likely that there will be more variation in estimates of that earnings. Therefore, in addition to firms generally seeing a reduction in spreads after the release of earnings, firms with larger standard deviations of earnings estimates should see larger declines in spreads. This reflects the greater reduction in uncertainty for the economic value of those firms and higher value of inside information.

Firm market value and the size of earnings surprises are all proxies for measuring the magnitude and importance of the information release. When the information released is especially novel or important, such as when announcing an earnings surprise or earnings for smaller firms, the information distance should decline relatively more. Clarke and Shastri (2000) provides a survey of the various measures of information asymmetry and the correlations between these measures. They also utilize earnings surprises and earnings estimate standard deviations as asymmetry measures. In addition to reviewing non-order flow (micro-structure) information asymmetry methods (e.g. investment and opportunity set measures and stock return measures), the paper has a detailed explanation and comparisons of the various micro-structure methods for calculating the adverse selection component of the bid-offer spread. They find these measures have a low correlation with the adverse selection components of the micro-structure methods, but they just use the end of the quarter measurements and therefore timing problems may reduce measured correlations.

### **2.1.3 Controlling for volume effects**

Volume is an important control variable in running these first difference estimation. Not only is there variation in daily volume, but earnings releases and conference calls are often near quarterly and annual portfolio re-balancing attracting larger volumes. Higher volume can reduce spreads through all three spread components. It can

reduce the adverse selection component by bringing more noise traders to the market. This allows market makers to dilute the costs per share traded of adverse selection by providing more uninformed trading counterparties among whom to spread those costs. However, if it also attracts more informed traders to market through lower transaction costs and greater anonymity, this effect may be reduced or eliminated.

Higher trading volume allows the fixed costs of market making to be spread over more trades, the order processing component should decline as well. They also decrease the time that market makers wait between trades. That is good for market makers because as it reduces the risk that they take a position to facilitate trade and then the price of the stock moves against them, leaving them with a loss on the assets they just traded. Consider an investor looking to sell 10,000 shares of a company stock when daily volume is 130,000 shares. If the arrival of buyer and sellers is equally likely then the market maker will on average have to wait an hour to reverse this position. That is, sell it to someone else. If volume were twice as large, then on average they would expect to wait half as long. That is less time for the share price to move against the firm. While prices could also move in their favor, if firms are risk averse then a risk premium must be built into the spread. It will decline as volume increases.

This paper assumes that the variable costs follow a linear technology and total order processing costs are distributed uniformly across trades by volume. Therefore, the order processing component should decline proportionally with the changes in inverse volume difference in (IVD). Where IVD is defined as follows:

$IVD_{i,t} = \frac{1}{vol_{t,i}} - \frac{1}{vol_{t-1,i}}$ .<sup>8</sup> This paper similarly assumes that if waiting costs and the adverse selection component vary with volume they do so proportionally to IVD.

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<sup>8</sup>As described, the order processing costs should be

$$order\ processing\ costs\ (volume) = fixed\ costs + Volume \cdot variable\ costs$$

Implying the order processing costs assessed to a single share under the two stage competition of Kreps and Scheinkman (1983) is:

$$Order\ Processing\ Costs\ per\ Share = \frac{fixed\ costs}{Volume} + variable\ costs$$

So the change in order processing costs are:

$$\Delta Order\ Processing\ Costs\ per\ Share = \frac{fixed\ costs}{Volume_{new}} + variable\ costs - \frac{fixed\ costs}{Volume_{old}} + variable\ costs$$

Then including the IVD in the regression distinguishes the benefits of greater volumes from the benefits from the change in information distance. Appendix D contains a proof that the average time a market maker must wait between trades declines with the inverse of the trading volume. It seems more convincing that the costs captured by the variable are the waiting time between trades rather than the fixed costs for order processing. Why should the fixed costs of market making be divided among the trades of each day, rather than spread among the trades of a much larger time period? The fixed costs of market making stem primarily from the capital investments. It would seem to make more sense to divide those costs among all the trades over the capital's useful life. To divide them up evenly among each day's trades is to lower the costs further when volumes are high and lower them when volumes are low.

There is a possibility of a problem with using the difference in inverse volume as calculated above. All other things equal, cheaper spreads (and therefore lower transaction costs) would bring more buyers and sellers to market. This creates a simultaneity problem where lower volumes lower spreads and spreads raise volumes. There may be multiple equilibrium pairs of volume and bid-offer spreads. However, as the data above shows, total spreads are small. The model predicts at best modest reductions of spreads of just a few percent of total spreads from large reductions in the information distance. To generate a large effect would require a large elasticity of demand for stock trading with respect to spreads. It seems implausible that big changes in volume could occur in response to these small transaction cost changes. If they did, the change in volume from lower spreads is rightly credited to the information release and the coefficients on volume changes represent an indirect effect of information releases on spreads.

Though not a perfect instrument, this elasticity can be estimated using stock market decimalization under the assumption that it reduced spreads without influencing trading volumes except through the mechanism of lower spreads. Surveying the evidence from the American and Toronto Stock Exchange decimalization, Goldstein and Kavajecz (2000) find an elasticity of between 0 and 5. This suggests that since these reductions amount to at most a few basis points change in transaction costs, volumes

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$$= \text{fixed costs} \cdot \left( \frac{1}{\text{Volume}_{\text{new}}} - \frac{1}{\text{Volume}_{\text{old}}} \right)$$

should be expected to change by less than 1% from the lower cost of trade alone. Given that dollar value of stock turnover is roughly the order of magnitude of firm value and taking into account the IVD estimates from later in the paper, this implies a miniscule indirect effect of reduced information asymmetry through the volume channel.

Other factors (e.g. focality) are more plausibly driving the observed variation in trading volume. It is also possible that if an earnings releases indicate a change of earnings growth and therefore suggesting a firm is transitioning to a value stock from growth one, the earnings release may cause the portfolio re-balancing and therefore cause higher volumes. This may happen, but is probably infrequent. For example, according to 2008 Morningstar data, the Russell 3000 Value Index has a turnover of 17%, the Russell 3000 Growth Index has a turnover of 18%, and the Russell 3000 Total Index has a turnover of 8%. This suggests that controlling for size, only about 10% of firms change from growth to value (or vice versa) a year.

## 2.2 The Models

### 2.2.1 Filings and earnings calls of ten large and ten small companies through the year

#### 2.2.1.1 Full sample

This model assumes a linear first difference form where the fixed effects are assumed to be eliminated except for the the information releases and the changes in trading volumes. A underlying economic model without rents is also assumed to hold. There are two indices,  $t$  is time and  $i$  the firm. For a given firm and day, there are four measures of the information change:

	<i>SEC Filings</i>	<i>Earnings Releases</i>
<i>Past</i>	$\Delta Days\ Since\ Last\ Filing_{t,i}$	$\Delta Days\ Since\ Last\ Earnings_{t,i}$
<i>Future</i>	$\Delta Days\ Until\ Next\ Filing_{t,i}$	$\Delta Days\ Until\ Next\ Earnings_{t,i}$

As discussed above, the components of the spread all could decline with volumes, so the difference in inverse volume (IVD) is also in the model. The variable  $Size_i$  is 1 if firm  $i$  is one of the 10 large firms and 0 if it is one of the 10 small ones. First difference are from the last business day to the one at day  $t$ . For example, when  $t$  is July 5th, 2005 then the previous business day is July 1st, 2005. The first difference is then the value on the fifth less the value on the first.

The paper estimates the following first difference OLS equation for the change in spread,

$$\Delta \% Spread_{i,t} = Size_i \cdot \left( \begin{array}{l} \beta_0 + \beta_1 IVD_{t,i} \\ + \beta_2 \Delta Days \text{ Since Last Filing}_{t,i} \\ + \beta_3 \Delta Days \text{ Until Next Filing}_{t,i} \\ + \beta_4 \Delta Days \text{ Since Last Earnings}_{t,i} \\ + \beta_5 \Delta Days \text{ Until Next Earnings}_{t,i} \end{array} \right) + (1 - Size_i) \cdot \left( \begin{array}{l} \beta_6 + \beta_7 IVD_{t,i} \\ + \beta_8 \Delta Days \text{ Since Last Filing}_{t,i} \\ + \beta_9 \Delta Days \text{ Until Next Filing}_{t,i} \\ + \beta_{10} \Delta Days \text{ Since Last Earnings}_{t,i} \\ + \beta_{11} \Delta Days \text{ Until Next Earnings}_{t,i} \end{array} \right) + \epsilon_{i,t}$$

where Market Value is the value of the outstanding shares of the firm at the end of fiscal year 2005. As an identification assumption this paper assumes that during the period of study, no other factors influencing the bid-offer spread changed.

The variables benefit from explanation. Immediately after the last earnings release, the information asymmetry is relatively small. As the quarter goes on, the information of outsiders gets staler. However, at first so does the information of insiders. They need time to gather information from distributors, customers, and auditors. They need to acquire that information and often especially focus on doing so at quarter end. So for outsider information is related to time from last release, while inside information is related to time until next release. The variable change in days since last earnings release



( $\Delta Days\ Since\ Last\ Earnings_{t,i}$ ) is normally is one day, unless there is a weekend (+3 days), holiday (+1 day), or and information release that day (0 days). In general, the variable change in days until next earnings release ( $\Delta Days\ Until\ Next\ Earnings_{t,i}$ ) works the same and with the opposite sign. But since firms have discretion on when they file (more than on when they close their books) the total of the two varies between firms ( $\Delta Days\ Since\ Last\ Earnings_{t,i} + \Delta Days\ Until\ Next\ Earnings_{t,i}$ ) varies between firms.

SEC filings should have the same timing relationship with information as earnings releases. However, they have an additional caveat. Some filings (e.g. 10K, 10K) are scheduled periodically, typically quarterly or annually. Others are unanticipated, filed in response to merger activities, material business events, and trading of stock by insiders (e.g. 8k). Investors and market makers could reasonably be expected to know the dates of anticipated filing events within an interval of a few days of discretion left to management. However, by their nature the unanticipated filings could not. Therefore, in the measure looking at days since the last filing, this is the time since any filing (anticipated or unanticipated) while the measure of time until the next filing is the time until the next expected filing.

Theory provides predictions of the signs of the  $\beta_j$ . If spreads were not systematically declining (or increasing) during the study period than the average change in spread should be zero and  $\beta_0$  and  $\beta_6$  would be zero. The longer it has been since an information release, the greater the information distance between insiders and outsiders. As such, the adverse selection component should increase and  $\beta_2, \beta_4, \beta_8,$  and  $\beta_{10}$  should positive. Those with inside information want to trade on it before it leaks or is publicly issued. Therefore, those with insider information are found disproportionately among market participants that cannot wait until after a release to trade. The longer it is until a public information release, the less likely a random participant is trying to trade on private information before that release. Because fields involving the change in number of days until the next release are negative when you get closer to a release, this predicts that  $\beta_3, \beta_5, \beta_9,$  and  $\beta_{11}$  should be negative.

### 2.2.1.2 Just days with filings

Using the same data as in the full sample model, it is possible to look only at those days where the firms file a document with the SEC. Instead of looking at the distance from information release events, this event study examines the difference before and after filing events. Again, there is an important distinction between unanticipated and anticipated filing events. This provides the following first difference model:

$$\Delta \%Spread_{i,t} = Size_i \cdot \begin{pmatrix} \beta_0 + \beta_1 \cdot UnanticipatedFiling \\ + \beta_2 \cdot AnticipatedFiling \\ + \beta_3 \cdot IVD_{t,i} \end{pmatrix} + (1 - Size_i) \cdot \begin{pmatrix} \beta_4 + \beta_5 \cdot UnanticipatedFiling \\ + \beta_6 \cdot AnticipatedFiling \\ + \beta_7 \cdot IVD_{t,i} \end{pmatrix} + \epsilon_{i,t}$$

The coefficients on the constant  $(\beta_0, \beta_4)$  should be weakly positive. On an average day without a release the information distance weakly increases and so should the spread. Since the other two indicators reflect the release of information, all other coefficients  $(\beta_1, \beta_2, \beta_5, \beta_6)$  should be positive.

### 2.2.2 Russell 3000 Companies with December FYE through high and low points of information distance in Q4

This model attempts to see differences in spreads from high and low points in the information distance stemming from the accumulation and release of company financial information. As discussed in detail in the data section, in this section the paper considers a universe of companies that belong to the Russell 3000 board stock market index in 2004 and 2005 with December fiscal year end dates. Companies sharing a fiscal year share a calendar of other earnings and reporting events. For example:

- September 30, 2005 – Q3 of fiscal year 2005 (FY05) ends
- November 9, 2005 – Q3 10-Q FY05 filing deadline
- November 14, 2005 – Greatest Distance from quarter end dates
- December 30, 2005 – Q4 of FY05 ends
- January 10, 2006 – All firms have compiled FYE 05 financials for internal use
- March 16, 2006 – Last day for on time filing of 10K for FY05

As such, the information distance of these firms should share seasonal dynamics.

Again, this paper uses a first difference estimation strategy, controlling for market value and IVD.

$$\Delta \%Spread_{t,i} = \beta_0 + \beta_1 IVD_{t,i} + \beta_2 Market\ Value_i + \epsilon_t$$

This model focuses on three timings and associated first differences, December 30th to January 10th, January 10th to March 16, January 10th to the date of 10-K filing (the next trading day). The first shows the change in spreads in response to insiders acquiring information on fiscal year end financials. The second shows the change in spreads from a day where only insiders know the true state of the financials to a day by which all firms should have filed their 10-K forms and everyone can know the true state.<sup>9</sup> The third more carefully controls for the timing of reductions in the information distance by looking at the first difference in spreads from when management knows to when firms file with the SEC and the information is public. The extent that the latter two results differ indicates the consequences of more precise timing.

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<sup>9</sup>Some firms file after this date but they do so in violation of Section 13(a) of the Exchange Act. The SEC can punish late filers with administrative proceeding. Markets also see this as a signal of a firm in financial disarray.

### 2.2.3 Changes in spread from earnings releases, earnings surprise, and estimate variation data

The previous two models try to proxy information distance changes with releases of market information. One criticism of this method is that much of the information released in SEC filings and even earnings announcements is either economically unimportant or economically important but not surprising. This third model uses earnings surprises and the breadth of earnings estimates in an attempt to quantify the impact of uncertainty and important information in spreads in a direct matter.

$$\Delta\%Spread_{i,t} = \beta_0 + \beta_1 EarningsPctSurprise + \beta_2 IVD_{t,i} + \beta_3 STDEV + \epsilon_{i,t}$$

Earnings percent surprise (*EarningsPctSurprise*) is defined by comparing analyst consensus estimates of corporate earnings with actual realized earnings. This measures the value of the insider information on earnings. When this gap is large insiders know something valuable about the firm compared with outsiders. *STDEV* (the standard deviation of analyst earnings estimates) measures the uncertainty around each firm's earnings. The greater this uncertainty the greater the expected asymmetric information between insiders and outsiders.

## 2.3 Data

If the order flow based measurements of adverse selection (like those of Huang and Stoll, Singh and Yerramilli, and GKN) are correct then measuring this change in the adverse selection component will be difficult. Total spreads are about 1.35% share values (.4% of large firms). Therefore, according to these measures the adverse selection component is approximately 14 basis points (about 4 basis points for large companies) of transaction cost. Changes in a variable of this magnitude will be subtle at best. Given that shares are quoted in dollars and cents (at least after the 2001 decimalization) and that median American share prices in the USA are in the \$40 a share range (Angel (1997)), a change of spread of a single basis point will be less than a penny. To detect these

subtle data requires a large and precise database. It is problematic to find companies with diverse enough ownership and liquid enough markets to do so.

Fortunately, the answer lies with choosing the firms that make up the Russell 3000 stock market index. This index is designed to mimic the behavior of the broad US equity market. Member companies must meet minimum liquidity requirements of at least 5.8 million shares of average daily trading volume. There is also a requirement for a minimum free float, the portion of the shares be held by outsiders. In 2005 the smallest market capitalization of company of the approximately 3000 in the index was \$250 million and increases to the giants of the US equity market Exxon Mobil and General Electric worth hundreds of billions of dollars.<sup>10</sup>

The first model tracks the twenty firms in my study from June 1, 2005 until June 31, 2006 in order to follow them across an entire year of SEC filings and earnings announcements. These were the ten smallest and ten largest firms in the Russell 3000 during that period with December fiscal year end (FYE), traded on the NYSE, that were also in the Compustat database of firm data and tracked by the Center for Research in Security Prices (CRSP) Database (daily volume). See Table 2.2 for the firms in this study and their sizes.

The second model uses two data sets to estimate the effect of year end financial information on the adverse selection component of the bid-offer spread. To calculate the data from December 30th to January 10th, and from January 10th to March 16th, it tracks the 2980 companies in the Russell 3000 Index list for 2005 (Company (2005)) at various points in the year. To simplify the timing and exchange specific issues, the paper restricts its sample to those companies traded on the NYSE (1,484 companies) with December FYE (1,155) in 2005. Also eliminated are those companies where Compustat could not provide trading volume or market capitalization data for the dates under study (127). This left a universe of 1028 firms.

In the second part of the second model, to calculate the data from January 10th to 10-K filing date, it attempts to control for firms entering and leaving the Russell 3000 by using firms that were any of the Russell 3000 membership lists from 2004 to 2006, and ignores exchange effects (an area for future work). Again choosing only firms with

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<sup>10</sup>Russel Indexes (2008)

**Table 2.2:** Firms in Year Long Information Release Study

<b>Ticker</b>	<b>Name</b>	<b>Size</b>
AEC	Associated Estates Realty Corp.	Small
AIG	American International Group, Inc.	Large
AP	Ampco-Pittsburgh Corp.	Small
BAC	Bank of America Corporation	Large
BDY	Bradley Pharmaceuticals Inc.	Small
C	Citigroup Inc.	Large
CRY	Cryolife, Inc.	Small
GE	General Electric Co.	Large
IBM	International Business Machines Corp.	Large
JNJ	Johnson and Johnson	Large
JPM	JPMorgan Chase & Co.	Large
LBY	Libbey Inc.	Small
MIG	Meadowbrook Insurance Group Inc.	Small
MO	Altria Group Inc.	Large
PFE	Pfizer Inc.	Large
RGR	Sturm, Ruger & Co. Inc.	Small
SEN	SEMCO Energy, Inc.	Small
SMP	Standard Motor Products Inc.	Small
SRI	Stoneridge Inc.	Small
XOM	Exxon Mobil Corp.	Large

December FYE, a universe of 2279 firms. If a firm changed its FYE, it was included if there was a year in the 2004-2005 sample in which the firm had a December FYE, but only for those years where it did so.

In the third model, this paper uses the complete set of publicly traded firms in the IBES earnings estimate system that were also in the Compustat, TAQ, and CRSP data-sets. It follows the convention of earnings estimate research to exclude financial and utility firms from earnings estimate analysis. That provides a universe of 4,830 firms that tracked from 1996 to 2003 on the business days before and after an earnings announcement. On average, the study has approximately three observations of annual earnings releases and estimate data per firm.

In all three models, the paper estimates the bid-offer spreads with stock quotes from the quotes sub-database from NYSE Trade and Quote (TAQ) database. Then, following rules for cleaning up quotation data proposed by Gibson et al. (2002), this paper removes obviously erroneous quotations. This required excluding trades outside of normal trading hours, those with negative bid-offer spreads, zero bids or asks, and those where the spread is larger than 10% of the average of the bid and ask prices. Further, because different trading rules operate on the opening of the stock market and the rest of the day, quotation data is further restricted to the period starting a half-hour after the open at 10:00 am until the regular market close at 4:00 pm. The paper calculates average daily quoted bid-offer spread for every five minute period of the trading day and then averaged these five minute average spreads across the 72 daily periods.<sup>1112</sup> The resulting average daily bid-offer spreads were used as the spread in the following analysis.

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<sup>11</sup>There may be a large distinction between the quoted and actual bid-offer spreads. Ellis, Michaely and O'Hara (2000) found that 12-14.5 percent of exchange trades execute inside the stated quotes and 5%-6% outside of the quotes. For trades on the electronic trading networks they found that just 31.25% traded at the bid and the ask. As long as the fraction of trades at the spreads and the nature of the discount received is independent of the size of spreads this will not change the results.

<sup>12</sup>I am grateful to Pu Shen of the Federal Reserve Bank of Kansas City who suggested this method of determining the daily average bid-offer spread.

**Table 2.3:** Comparing Predicted and Actual Regression Coefficient Signs

$\beta_{Field}^{Size}$	Coefficient	Predicted Sign	Actual Sign
$\beta_{Constant}^{Large}$	$\beta_0$	Zero	Positive
$\beta_{Constant}^{Small}$	$\beta_6$	Zero	Positive
$\beta_{Since\ last\ file}^{Large}$	$\beta_2$	Positive	Positive
$\beta_{Since\ last\ earn}^{Large}$	$\beta_4$	Positive	Negative
$\beta_{Since\ last\ file}^{Small}$	$\beta_8$	Positive	Negative
$\beta_{Since\ last\ earn}^{Small}$	$\beta_{10}$	Positive	Negative
$\beta_{Until\ next\ file}^{Large}$	$\beta_3$	Negative	Negative
$\beta_{Until\ next\ earn}^{Large}$	$\beta_5$	Negative	Negative
$\beta_{Until\ next\ file}^{Small}$	$\beta_9$	Negative	Positive
$\beta_{Until\ next\ earn}^{Small}$	$\beta_{11}$	Negative	Positive
$\beta_{IVD}^{Large}$	$\beta_1$	Positive	Positive
$\beta_{IVD}^{Small}$	$\beta_7$	Positive	Positive

## 2.4 Analysis

### 2.4.1 Results for 20 companies tracked through the year

Table 2.5 shows the results of the general model above. The model fits the data weakly though that is to be expected from the noise in the data and the relatively few data-points where there is significant movement in the independent variables.

Table 2.3 compares the signs of the regression predicted from theory with the actual results. The signs also do not appear to be correct. Only 5 of the 12 regression coefficients have the desired sign and none are significant in the desired way. Inverse dollar volume is positive as desired for both sizes (only significant for large firms), but the coefficient is very different in magnitude. Part of that is an artifact of the measure. Larger firms tend to have much higher trading volume, and if there are both fixed and variable costs of trade then eventually the variable costs will dominate and so the effect size will vary. However, when the regression is rerun in log form we see that again the change in volume is only significant for large firms but now it has the correct sign. The overall fit of the log model is worse.

Table 2.5 shows the results of the model where the paper restricts analysis to days when an SEC filings occurs. Again the model works better for large firms than small ones. Because the constant term is positive, on a day with a release the average



**Table 2.4:** Predicting Percent Change in Bid-Offer Spread: Tracking Companies Through the Year

VARIABLES	(1) IVD		(2) Log Dollar Volume $\Delta$	
	Larger Firms	Smaller Firms	Larger Firms	Smaller Firms
$\Delta$ Days Since Last Release Date	-2.790e-06*** (7.581e-07)	-1.380e-06 (4.189e-06)	-2.766e-06*** (7.684e-07)	-1.811e-06 (4.291e-06)
$\Delta$ Days Since Last Filing Date	-2.259e-06 (2.807e-06)	-4.624e-06 (1.538e-05)	-2.002e-06 (2.825e-06)	-5.014e-06 (1.525e-05)
$\Delta$ Days Until Next Release Date	-1.351e-06* (5.530e-07)	-1.267e-05* (6.419e-06)	-1.355e-06* (5.590e-07)	-1.268e-05* (6.443e-06)
$\Delta$ Days Until Next Filing Date	-2.974e-07 (6.959e-07)	2.250e-06 (6.146e-06)	-3.035e-07 (6.605e-07)	2.018e-06 (6.124e-06)
Inverse Volume Difference	1.682e+05*** (4.587e+04)	2.921e+00 (3.767e+00)		
$\Delta$ Log Dollar Volume			-4.893e-04*** (1.463e-04)	-2.882e-04 (2.548e-04)
Constant	-1.445e-06 (9.507e-06)	-6.993e-06 (7.004e-05)	-1.490e-06 (9.630e-06)	-6.176e-06 (7.002e-05)
Observations	2730	2661	2730	2661
$R^2$	0.045	0.002	0.021	0.002
Adj. $R^2$	0.0437	-0.000103	0.0188	0.000373

Robust standard errors in parentheses

\*\*\* p&lt;0.001, \*\* p&lt;0.01, \* p&lt;0.05

**Table 2.5:** Predicting Percent Change in Bid-Offer Spread: Just Days with SEC Filings

VARIABLES	(1)	(2)
	Larger Firms (1)	Smaller Firms (0)
First Difference in Inverse Dollar Volume	166813.90565** (61383.68810)	-0.54279 (14.14526)
Anticipated Filing	-0.00011* (0.00005)	-0.00067 (0.00116)
Unanticipated Filing	-0.00012 (0.00006)	-0.00062 (0.00120)
Constant	0.00014* (0.00007)	0.00046 (0.00122)
Observations	1081	386
Adj. $R^2$	0.05803	-0.00641
$R^2$	0.06064	0.00143

Robust standard errors in parentheses

\*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$

First Difference in Inverse Dollar Volume - IVD measured from day with SEC filing to trading day before.

Anticipated Filing - dummy variable for the release of an anticipated SEC filing.

Unanticipated Filing - dummy variable for the release of an unanticipated SEC filing.

large firm's spread increases by .2-.3 basis points which is the opposite of what theory predicts. It is only when both types of releases occur that the regression predicts a decline of .9 basis points. For small firms a release is associated with an average spread reduction of 2 basis points or 8 basis points. That is good and consistent with the prediction but none of the coefficients are statistically significant. A natural extension to this project is to break the filings into more and less important ones and track their influence separately, perhaps in a multi-level model. Appendix E shows this model run on all days, not just those where there are information releases.

#### 2.4.2 High information distance results for Russell 3000 firms

Table 2.6 examines the change in spreads from a time when even management is ignorant of the the firm's true profitability (at the end of the quarter on December 30th) to a short while later (January 10th) when management learns true profitability

**Table 2.6:** Changes in Information Distance from Creating Year End Financial Data  
**First Difference in Percent Spread From December 30, 2005 to January 10, 2006**

Log of Firm Size	-0.05
	-1.58
First Difference in Inverse Dollar Volume	-1,536.56
	(10.10)**
Constant	1.05776
	-1.59
Observations	1036
R-squared	0.01
Robust t statistics in parentheses	
* significant at 5%; significant at 1%	51.05
F( 2, 1033)	
Prob > F	0
Average Log of Firm Size	21.68
Average First Difference in Inverse Dollar Volume	1.88E-07
Average Percent Change in Spread	4.45%

but such information is not yet released.<sup>13</sup> The constant term has the expected positive sign. This is consistent with the theoretical predictions in light of a growth in the information distance. However, it is insignificant. The coefficient on firm size is negative, which is consistent with larger firms seeing smaller increases in spreads from insiders accumulating information. However, market capitalization is not significant. As in the earlier regressions, IVD is significant, which drives the high F-statistic.  $R^2$  values are again low, as the data has a lot of noise.

The results of looking at the spread changes from January 10th to March 16th are in Table 2.7. This is a broad comparison to see if the end of earnings season tightens spreads as the information distance declines. Again the regression coefficients have unexpected signs. The constant is positive, not negative as expected from a decrease in information distance. This indicates that spreads increased from January 10th to March 16th for an average firm. The coefficient on log firm size is negative, indicating

<sup>13</sup>The date January 10th was picked in consultation with professionals familiar with the calendar of corporate financials. It represents a date by which the corporate accountants of the vast majority of firms have had adequate time to compute the financials after the close of the quarter and fiscal year. The author knows of no industry surveys providing firm specific timing on internal financials generation.

**Table 2.7:** Changes in Information Distance from Releasing Year End Financial Data without Specific Timing (March 16th)

**First Difference in Percent Spread From January 10, 2006 to March 16, 2006**

Log of Firm Size	-0.03
	-1.51
First Difference in Inverse Dollar Volume	3,764
	-1.01
Constant	0.84
	-1.71
Observations	1036
R-squared	0.01
F(2,1033)	1.62
Prob > F	.1988
Robust t statistics in parentheses	
* significant at 5%, ** significant at 1%	
Average Log of Firm Size	21.67686
First Difference in Inverse Dollar Volume	4.95E-07
Average Percent Change in Spread	12.52%

larger firms experienced a lesser increase in spreads over the period. That means that large firms experienced a smaller change in spreads over the study, which is as desired. Unfortunately, this change was in the wrong direction. The IVD has the correct sign this time, but it is not significant. No coefficients are statistically significant, nor is the joint F-statistic.

Finally, Table 2.8 compares the spread changes from January 10th to 10-K release date. These are the clearest results in the study, with the highest F-statistics and the most significant coefficients with the desired signs. Column one in Table 2.8 measures the size effect with the log of firm size, while column two uses the decile of firm size. The results are similar. The IVD measure is significant and positive, indicating that an increase in volume (decrease in IVD) decreases spreads. The coefficients on the two size variables are positive and significant, indicating that larger firms see a smaller reduction in spreads. Finally, we see the constant terms are negative and significant, indicating that spreads decline over the study period. Because of the high F-statistics as well as the significant coefficients, there is evidence to reject the null hypothesis that there is no reduction in the adverse selection component between January 10th and the date of filing the 10K. Interpreting this as a linear causal effect, information in the 10K

**Table 2.8:** Changes in Information Distance from Releasing Year End Financials with Specific Timing**First Difference in Percent Spread From January 10, 2006 to 10K Filing Date**

	(1)	(2)
First Difference in Inverse Dollar Volume	0.28 (5.28)**	0.29 (5.26)**
Log of Firm Size	0.00361 (11.04)**	
Firm Size Decile		0.00045 (2.71)**
Constant	-0.08515 (13.01)**	-0.01625 (17.49)**
Observations	3997	3997
R-squared	0.06	0
F( 2, 3994)	75.83	16.83
Prob > F	0	0
Robust t statistics in parentheses		
* significant at 5%, ** significant at 1%		
Average DIV	-1.35E-05	-1.35E-05
Average Size on Jan 10	\$20.10	5.5
Effect For Firm of Average Size	-1.26%	-1.63%

declines spreads by about 1.5%. Note again that spreads are small. For the typical firm in this study with a 0.6% bid-offer spread, this amounts to a reduction of the spread by 0.9 basis points to about 0.59%. That is still a tiny decline when we consider that this study concerns the consequences of the filing of the most important annual financial document.

### 2.4.3 Earning surprise results for IBES sample

Table 2.9 shows the results of the third model connecting earnings estimates and surprises to changes in percent spread. The signs are correct for fraction surprised, larger surprises reduce more uncertainty. Larger standard deviations from the IBES estimates is associated with higher spreads after the release which is the opposite sign from the prediction from the theory. Contrary to the prediction, the information distance indicators of the size of the surprise and the standard deviation of the estimates are not

**Table 2.9:** Earnings surprises do not reduce bid-offer spreads

Predicting Change in Percent Bid-Offer Spread with Estimate and Surprise Data						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	IVD	Log Vol.	IVD Log Size	Log Vol. Log Size	IVD Size Decile	Log Vol. Size Decile
Earnings Fraction Surprised	-4.9e-06 (7.9e-06)	-4.9e-06 (7.818e-06)	-5.7e-06 (7.873e-06)	-5.583e-06 (7.823e-06)	-5.9e-06 (7.872e-06)	-5.8e-06 (7.822e-06)
Standard Deviation of Earnings Estimates	6.4e-07 (1.8e-05)	3.4e-06 (1.748e-05)	1.8e-06 (1.759e-05)	4.4e-06 (1.748e-05)	2.0e-06 (1.759e-05)	4.6e-06 (1.748e-05)
Inverse Volume Distance	3.3*** (4.575e-01)		3.3*** (4.584e-01)		3.2*** (4.582e-01)	
$\Delta$ Log \$ Volume		-1.9e-03*** (1.146e-04)		-1.9e-03*** (1.147e-04)		-1.9e-03*** (1.147e-04)
Log of Firm Size			1.8e-04* (7.216e-05)	1.7e-04* (7.162e-05)		
Firm Size Decile					6.7e-05*** (1.985e-05)	6.2e-05** (1.970e-05)
Constant	-1.6e-04** (5.706e-05)	2.0e-04** (6.117e-05)	-1.2e-03** (4.166e-04)	-7.7e-04 (4.149e-04)	-5.3e-04*** (1.234e-04)	-1.4e-04 (1.254e-04)
Observations	16823	16823	16823	16823	16823	16823
$R^2$	0.003	0.016	0.004	0.016	0.004	0.016
Adj. $R^2$	0.003	0.016	0.003	0.016	0.0036	0.016

Standard errors in parentheses\*\*\* p<0.001, \*\* p<0.01, \* p<0.05

statistically significant. IVD has a positive sign so greater volume decreases spreads and the negative sign of the difference in the log volume has the largely same interpretation.<sup>14</sup> Assuming that the coefficient point estimates are the true values, since the average standard deviation of an earnings estimate in my sample is .3, this model predicts that the shares of a typical firm experiences a decrease in spreads of 1.4 basis points. That is consistent with the results in Table 2.8 which found that 10-K releases have a 1.1 basis point effect. That is close to the lower threshold of economic significance established earlier at the limits of the significant digits of the data. This is at best moderate evidence of a weak adverse selection component. In total, with small F statistics and  $R^2$ , this model is not capturing a lot of the variation in spreads. This paper provides evidence for skepticism that a meaningful reduction in spreads is occurring with these information releases. Appendix F shows similar results for alternative definitions of earnings surprises.

## 2.5 Conclusions

If there is an adverse selection component of the bid-offer spread it should vary with the information distance between the informed and uninformed. However, these results suggest show that often it does not do so. When it does, such an effect is weak, no more than 2 basis points of transaction cost in statistically significant models. Instead, this paper finds that information releases are not generally associated with reductions in the bid-offer spread. There are several reasons why this could be. One is that the information distance is time-invariant. However, for the reasons discussed above, this is implausible. Another possibility is that these measures are poor indications of the quantity and value of inside information. That is more likely. However, if earnings surprises, regulatory filings, and earning releases do not reduce the information difference between insiders and outsiders, then that raises additional questions. What purpose do regulatory filings serve if not to inform outsiders about insider conduct? Why create or read fil-

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<sup>14</sup> $\forall A, B > 0$  if  $A > B$  then  $\frac{1}{A} - \frac{1}{B} < 0$  and  $\log(A) > \log(B) \Rightarrow \text{sign}(\log(A) - \log(B)) = -\text{sign}(\frac{1}{A} - \frac{1}{B})$ . However, since  $\log(\frac{1}{A} - \frac{1}{B}) = \log(\frac{1}{A}) + \log(1 - \frac{A}{B}) = \log(\frac{1}{A}) + \log(\frac{B-A}{B}) \neq \log(\frac{1}{A}) - \log(\frac{1}{B})$  the scale differs by more than just a log transformation. However, since log differences may be more intuitive to the reader and the results are similar, they are included.

ings that do not inform? Is an earnings surprise a surprise if it doesn't inform? What is the asymmetric information market makers are protecting themselves from if it is not the information in these calls, filings, and releases? The cleanest interpretation is that these releases do decrease the information distance, but that the bid-offer spread is not falling because there is no adverse selection component in the spread or it is minimal. This research suggests that the enormous volume of noise trading and the regulations on insider trading are sufficient to protect the market makers from the trading strategies of insiders.

It is still unclear what part of the estimation method of inventory accumulation is breaking down. The studies have carefully estimated spreads, so measurement error seems unlikely. They are somewhat dated at this point, so it could be a phenomenon that once existed in US equity markets but no longer does. That too seems implausible because while markets have deepened since the late 1990's, there does not appear to be a declining trend in the proportion of spreads attributable to these methods over time. Indeed the opposite, with later studies showing higher proportions than earlier ones.

A stronger possibility is model misspecification error as (Neal and Wheatley, 1998) and Clarke and Shastri (2000) have argued. Unfortunately, that is a large category of problem. One possibility is that contra to the assumption of this paper and the papers it addresses, that the return process is not independent of the stock of noise traders. Another plausible form of misspecification is that market makers are making rents off of their positions. They may then use these rents to smooth the spread in the face of insider information, explaining why this paper finds little movement in response to inside information. Further, since inventory accumulation methods estimate the adverse selection component with the regression residual, this exaggerates the adverse selection component because it would also include rents.

## **2.6 Future Research**

As discussed above, the difference in inverse volume measure (and log volume) used to proxy for the varying costs of trade is subject to some criticism as suffering from an endogeneity problem. One possible way of addressing this criticism is to use



not the volume from the dates in the study, but the average of several nearby dates. Another possibility is to do a joint estimation of changes in trading volume and changes in spread.

With more firms in the study and a time-line also indicating the size of releases, the possibility exists of formulating and testing hypotheses about information acquisition and release. For example, do spreads show that insiders smoothly accumulate an information advantage over market makers? Is that information reaching markets in discrete chunks on release dates or is it leaking to the market in the days before the scheduled release? Similarly, there is a natural calendar dictating when insiders see sales and earnings data dictated by year, month, week end dates. Do insiders accumulate information smoothly or discontinuously?

Another area for future research concerns the behavior of corporate insiders. We know that corporate insiders rarely purchase stock and instead receive most of their holdings as compensation. That suggests that protections against adverse selection by market makers may be asymmetric, making them more concerned with the arrival of sell orders than buy orders. This could motivate alternative order flow based econometric measurements of spread components.

One serious problem with continuing this line of research is the decline in the interpretation of NYSE-TAQ spread quotes as the true spreads faced by market participants. According to Smith (2010), TAQ data does not include electronic communication network (ECN) trades not settled with the exchange nor non-displayed liquidity pools (dark pools). This is an age where the market share of the NYSE reported market share has declined to from about 83% in 1995 (estimated by Blume and Goldstein (1997)) to 31% in 2012 (from Euronext (2012) estimates). Dark pools were not a major force in trading in the 1990's but today some estimates have NYSE share of volume total volume including these pools as low as 25%. Further compounding this problem is that many trades on the exchanges take place within the quoted spreads. No doubt they remain indicative of rough trading costs but their ability to precisely measure them is in serious doubt. In addition, Goldstein and Kavajecz (2000) and Chordia et al. (2011) document respectively the decline in market depth for securities after decimalization and the growth of ECN. In total, it may be problematic to interpret these spreads as precise

estimates of a stock's liquidity or even as a precise estimate of the cost of transacting. Overcoming these limitations of the TAQ data is an important avenue for research in this area.

## **Chapter 3**

# **International Employment and the Business Cycle: New Stylized Facts with an Application to the Great Moderation**

### **3.1 Introduction**

Since documenting the substantial reduction in the volatility of output in the early 1980s, empirical research has uncovered a widespread reduction in the volatility of macroeconomic time series roughly coinciding with that in output. Stock and Watson (2002) and Sensier and van Dijk (2004) examined the break in volatility in more than 100 US macroeconomic time series. The vast majority coincided with the decline in output volatility. The mechanisms underlying this decline remain controversial and falls broadly into three categories; i) good luck, ii) good policy, or iii) structural change. The “good luck” hypothesis posits the recent period of stability is due to a string of smaller than normal exogenous shocks. This represents the alternative hypothesis to the other methods considered, which we discuss in turn. The “good policy” hypothesis suggests the improvements in monetary policy have “tamed” the business cycle.<sup>1</sup> Finally, the

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<sup>1</sup>See Galí and Gambetti (2009) for a brief survey of these mechanisms.

“structural change” hypothesis posits a fundamental change in institutions (e.g. labor markets) or household preferences has altered the business cycle.

The regime shift to Volcker’s intense focus on inflation in the early 1980s coupled with increased transparency at the Federal Reserve and rapid innovation in macroeconomic theory all point to increasingly effective monetary policy.<sup>2</sup> Note that the decline in inflation volatility is not restricted to the US. Cecchetti *et al.* (2006) examine 24 countries and find that in 11 countries both inflation and output volatility fell. In an additional 9 countries inflation volatility fell substantially while output volatility rose modestly or was unchanged. Importantly, none of the countries saw an increase in both inflation and output volatility.

DSGE models provide primarily support for good policy results. Theoretically, Clarida *et al.* (2000) show that sufficiently passive monetary policy is unable to overcome individuals’ expectations. Consequently expectations become self-fulfilling resulting in multiple-equilibria. In their calibrated model, Volcker shifted the US from an indeterminate to a determinate equilibrium thereby reducing the volatility. Lubik and Schorfheide (2004) subsequently provide an estimator that is valid for both determinate and indeterminate regimes. They apply their estimator to a DSGE model and find that the pre-Volcker regime was in an indeterminate equilibria.

VAR models mostly point to good luck. For those VAR models finding a role for monetary policy, the effect is not large and depends upon the greater role of demand shocks impacting the economy.<sup>3</sup> Internationally, Canova *et al.* (2007) consider the US, UK, and Euro Zone in a structural Time-Varying Parameter (TVP)-VAR. They find international co-movement in inflation and nearly independent output which is inconsistent with a good policy story. Furthermore they find that the interaction of supply and monetary shocks drive output volatility in the US, whereas it is demand and monetary shocks in the Euro Zone, and solely supply shocks in the UK.<sup>4</sup>

One possible reconciliation between the DSGE and VAR results is that VARs

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<sup>2</sup>In particular the departure from large-scale macroeconomic models following the Lucas’ (1976) critique and Sims’ (1980) cogent case for VAR analysis. The empirical success of Volcker-Greenspan policy culminated in the now-standard Taylor (1993) rule for monetary policy.

<sup>3</sup>See, e.g., Boivin and Giannoni (2006).

<sup>4</sup>Further VAR results include Primiceri (2005), Sims and Zha (2006), and Gambetti, Pappa, Canova (2008).

fail to account for multiple equilibria. Using the Lubik and Schorfheide (2004) estimator, Benati and Surico (2009) find that the difference between DSGE and VAR results are due to the failure of VAR models to account for multiple equilibria pre-Volcker. They show that VAR results with indeterminacy are observationally equivalent to those without, however only the former implies a role for monetary policy.

Despite their theoretical advantages, DSGEs have estimation problems as well. Canova (2006b)

(2006a) shows that the Benati and Surico (2009) critique is specific to their methodology and provide a model with determinacy that is able to reproduce the dynamics with indeterminacy. Their more general conclusion is that greater care needs to be taken in order to match the identifying restrictions in the structural VAR to the underlying DSGE model. Furthermore, Canova and Sala (2009) show that there are substantial identification problems with DSGEs themselves.

Beyond the technical difficulties in estimation, there are two further problems for the good policy hypothesis. First, it is difficult to point to examples of monetary regime change outside of the USA under Volcker and the UK's exit from the European Exchange Rate Mechanism (ERM) in 1992. Not only is the UK the only other example, but Benati (2008) finds that monetary policy cannot even explain the UK's volatility dynamics. Second, the recent financial crisis is marked by its lack of monetary policy change. Whereas Volcker's chairmanship marked a clear change in monetary policy and the beginning of the Great Moderation, Bernanke was appointed to extend the successful Volcker-Greenspan regime. With plausible continuity in policy there must be a non-policy explanation for the Great Moderation's abrupt end.

Several structural (non-monetary) policy changes have been proposed; inventory management, financial frictions, and labor frictions. Improved inventory management was originally proposed in McConnell and Peres-Quiros (2000) and Kahn and McConnell (2002). This view has fallen out of favor based on both theoretical and empirical grounds.<sup>5</sup> Financial frictions have not undergone the same sort of scrutiny in this context. One example is Justiniano and Primiceri (2008) who propose a large-scale DSGE model with time-varying volatilities that accounts for the pre-Volcker indetermi-

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<sup>5</sup>For theoretical arguments see Maccini and Pagan (2003), Kahn and Thomas (2007). For empirical results see Ahmed et al (2004), Ramey and Vine (2006).

nate equilibrium. They find that the majority of the decline in output volatility is due to a shock which they interpret as representing financial frictions. However they stress this is, at best, a reduced form interpretation. Explicitly including financial frictions will alter the model beyond just the investment relation. While this may explain the onset of the Great Moderation, it does not explain its end. If anything, financial services continued to be deregulated and financial innovation expanded the universe of credit instruments during this time.<sup>6</sup> The Great Moderation was punctuated by several financial crises prior to 2008.<sup>7</sup> Perhaps the reduction of explicit financial frictions was offset by a rise in systemic risk that is not captured by the reduced form of the model. We leave that for future research.<sup>8</sup>

The remaining hypothesized structural change is labor market frictions. Labor represents two thirds of national income.<sup>9</sup> Consequently, a small change in labor frictions could cause large changes in aggregate fluctuations.

In addition to the decline in hours volatility, there are three additional stylized facts in the literature. The first is the large decline in the correlation between labor productivity and output in the US that coincides with the Great Moderation. Kydland and Prescott (1982) used the high correlation between labor productivity and output to support the real business cycle (RBC) model. In the RBC model positive aggregate technology shocks increase the marginal productivity of labor leading to an increase in employment during booms, and vice versa during recessions. However, the rapid decline in the correlation to near zero in the mid-1980s undermined their supporting stylized fact. Subsequent research has tried to revive the role of technology shocks in driving the business cycle by introducing frictions with mixed results.<sup>10</sup> Second, Stiroh (2009) documents a stark decline in the correlation between labor productivity and hours in the US also coinciding with the Great Moderation. Furthermore, this result holds using both

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<sup>6</sup>For a survey of the scope and benefits of financial innovation, see Litan (2010)

<sup>7</sup>Most notably LTCM in 1998 and the S&L Crisis in the mid-1980s.

<sup>8</sup>Stock and Watson (2005), in a VAR, study the international business cycle for the G7 and find that international shocks have declined. This may be due to the reduction in international trade barriers and globalization of finance. Additionally the countries seem to have split into two cyclically coherent groups: English and non-English speaking countries.

<sup>9</sup>This is true internationally, see Gollin (2002).

<sup>10</sup>For early arguments for and against the RBC model see the Summer 1989 issue of *The Journal of Economic Perspectives*. Specifically, Mankiw (1989) and Plosser (1989). A brief review of the merger between the RBC and the search and matching literature can be found in Ramey (2011).

aggregate and disaggregate manufacturing data. A final stylized fact was uncovered by Galí and Gambetti (2009). They consider a model with labor productivity and output in a time-varying parameter (TVP-) VAR with stochastic volatility. They find that the volatility of hours and output both decline in the US, however hours declined less than output. Interestingly they also calculate the correlation between labor productivity and output and find that it remains significantly pro-cyclical. However they do not discuss this anomaly.

We provide three contributions. First, the stylized facts given above are obtained using different data sets and different statistical methodologies. There are several methods to deal with the nonstationarity induced by the structural change of the Great Moderation. We find, in the US, most of the labor market stylized facts are robust to statistical method. The exception is the correlation between labor productivity and output, the linchpin of the RBC model.

Second, we extend the set of stylized facts to thirteen OECD countries using a new data set constructed by Ohanian and Raffo (2011). Previously, international labor data was only available on a capitation employment rather than hourly basis. Since modern macroeconomic models find support for adjustment of both the intensive and extensive margins, we would expect this to be an important innovation. Furthermore the extensive literature in the US utilizes hourly data. This data provide the first comprehensive means of comparing labor and output internationally. We document significant international heterogeneity and provide a new set of stylized facts.<sup>11</sup>

Finally, we consider the model of Galí and van Rens (2010) as a possible explanation for the observed heterogeneity. Galí and van Rens (2010) provide a theoretical model that is able to match employment and output statistics solely using labor market frictions. Specifically, they consider three empirical regularities in US employment: i) the decline in the procyclicality of labor productivity with respect to output and labor input [Stirolh (2009), Uhlig (2010)], ii) the increase in the volatility of labor input relative to output [Galí and Gambetti (2009)], and iii) the rise in the absolute and relative volatility

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<sup>11</sup>Ohanian and Raffo (2011) look at similar moments, however they use only a single method and a single breakpoint. They estimate the HP filter over two subsamples and calculate the difference. This will be discussed in more detail in section 3.2.2. Their use of a single breakpoint corresponding to the US change in 1984 is inappropriate given the asynchronous onset of the Great Moderation. See, e.g. Blanchard and Simon (2001) and Stock and Watson (2005).

of the real wage [Galí and van Rens (2010)]. Their model allows for endogenous effort and labor adjustment costs. Calibrated to US data, moving from a completely rigid to a completely flexible labor market generates all of the stylized facts, including a reduction in output volatility. However, they caution that the calibrated model only delivers a modest reduction in output volatility.

In addition, their results are illustrative rather than quantitative. The US labor market was never completely rigid and is not completely flexible, hence whether the US experienced an economically meaningful shift in labor market frictions remains an empirical question. The stylized facts we uncover thus predict a change in labor market frictions within their model. We compare those predictions to a set of labor market frictions using data collected by the Amsterdam Institute for Advanced labor Studies (AIAS). We find that these measures do not match the predictions and tentatively conclude that a reduction in labor market frictions is not the main driver of these moments internationally. However this does not refute the possibility that it could still apply to the US. We then suggest an alternative explanation of the data.

The paper proceeds as follows. Section 3.2 introduces the statistical methods and applies them to the US data. Section 3.4 then considers the international evidence and highlights those countries consistent with the US experience. Section 3.5 presents the labor market frictions and possible explanations for our international results. Section 3.6 concludes.

## **3.2 US Stylized Facts**

To begin we establish the stylized facts found in the literature for the US. These stylized facts are statements on the non-stationarity of the respective series. To be precise, the series are typically assumed to be stationary in two subperiods with a one-time structural break. However, that is not the only possible form of non-stationarity. Consequently, we consider whether the stylized facts are robust to alternative specifications of non-stationarity. It is critical that the stylized facts we use to build models are robust to statistical method. To quote den Haan (2000): “Macroeconomic models are judged



on their ability to reproduce key correlations in the data. Using these kind of empirical results to judge theories presupposes that there is a set of correlations upon which everyone can agree.” In particular, we allow for continuous change in the second moments.

In addition to the decline in output volatility we consider two stylized facts found in the literature. These are that i) labor productivity has become less procyclical with respect to output and labor input, and ii) the volatility of labor input relative to output has increased. Let  $y_t$  denote output,  $\ell_t$  labor input, and  $x_t = y_t - \ell_t$  be labor productivity, all in logs. Then the stylized facts can be expressed as:

$$\begin{aligned} \sigma_y &\downarrow \\ \text{corr}(x_t, y_t) &\downarrow \\ \text{corr}(x_t, \ell_t) &\downarrow \\ \frac{\sigma_\ell}{\sigma_y} &\uparrow \end{aligned}$$

Our techniques fall into two categories: i) first estimate the structural break date, and then compare the two sub-periods, and ii) estimate a continuous, time varying measure of the covariance matrix. In the first case, each subperiod is stationary and we compare a set of statistics restricted to each subperiod. In other words, the only dynamic is the change across the regimes.

While this two stage estimation is relatively simple an important caveat deserves mention. Cogley and Sargent (2005) and Benati (2007) provide Monte Carlo evidence for the lack of power in state-of-the art structural break tests when the true model is a random walk. Unfortunately, in our application labor productivity is typically assumed to follow a random walk, e.g. identification of technology shocks from long-run restrictions on labor productivity [Galí (1999)]. In fact, Benati (2007) concludes that “when time-variation in equilibrium productivity growth does take place, it takes place most likely gradually...so that the best way of analysing it is via time-varying parameters models, rather than via break tests.”

Consequently, we allow continuous variation and use the entire time series to estimate the dynamics. This allows a much more detailed view of the dynamics, rather

than a simple sign comparison. An additional benefit noted by Benati (2007), is that allowing varying VAR coefficients is a good approximation even if there is but a single break whereas first estimating a break and comparing subperiods is valid only if trend-breaks is the correct DGP. However, this requires estimating a much larger, more complex model and the time-varying parameters are therefore less precisely estimated.

In the rest of this section we will present our five statistical models and apply them to the US. Our goal is to ascertain whether each method delivers all of the US stylized facts found in the literature. This documents a baseline to compare international results to in section 3.4. Before summarizing the models we first present our data.

### 3.2.1 Data

The data are GDP and hours for thirteen countries roughly over the period 1960q1-2010q4, with the analysis limited by the availability of hours data. Table 3.2.1 provides the time periods hours per capita are available for each country. GDP data are real chain-weighted indices. Hours are establishment data. Both are constructed to match National Income and Product Account (NIPA) conventions. In addition, both series are standardized by the working age population 15-64 years and converted to logs. Labor productivity is given as the log difference between GDP and hours.

The data is from a new publicly available dataset constructed in Ohanian and Raffo (2011).<sup>12</sup> They assemble annual data from the OECD, national statistical agencies, and Groningen Growth and Development Centre (GGDC). They then backcast these official series using quarterly International Labor Organization (ILO) and, rarely, OECD Main Economic Indicators (MEI) data on hours. They use the method from Deaton (1971)<sup>13</sup> to ensure the quarterly series matches the more accurate annual time series. The exact details of its construction can be found in Ohanian and Raffo (2011), but we note the estimation used to construct hours does not use GDP.

Note that Brügemann, Hagedorn, and Manovskii (2010) and Hagedorn and Manovskii (2011) find that the choice of labor input has significant effects on the labor market statistics in the US. Specifically, there are significant differences between the

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<sup>12</sup>The data was kindly provided by the authors.

<sup>13</sup>This is used, for instance, to construct the Industrial Production series.

**Table 3.1:** Hours per Worker: Sample Periods

Australia	1970-2010		Italy	1960-2010
Austria	1965-2010		Japan	1960-2010
Canada	1960-2010		Norway	1960-2010
Finland	1960-2010		Sweden	1975-2010
France	1960-2010		UK	1971-2010
Germany	1960-2010		U.S.	1960-2010
Ireland	1960-2010			

Current Population (household) Survey and the more popular Current Employment (establishment) Survey. Ohanian and Raffo (2011) use the latter definition. We admit that the results may vary with alternative definitions of employment, however we make several observations. First, prior to this data set, European labor and productivity analyses have predominantly relied upon per-worker concepts whereas US research has focused per-hour measures. Insofar as we believe stylized facts in the labor market correspond to adjustments along both the intensive and extensive margins, the most appropriate measure is hours data. Second, for the international comparisons to be sensitive to the choice of series the discrepancy between the series would have to vary systematically across countries. Third, this is the first internationally consistent data set for hours. While the results may be sensitive to the choice of household versus establishment survey, neither was previously available. Lastly, the sensitivity has only recently been examined in the US. Using the much more popular establishment data allows us to compare our results to a much larger US literature.

### 3.2.2 Filters and Rolling Window

Our first method considers two detrending methods that are used to extract the business cycle: the Hodrick-Prescott (HP) and Baxter-King (BK) filters<sup>14</sup>. The former can be formulated as a ridge regression with a smoothing parameter ( $\lambda$ ), while the latter directly considers the frequency domain via a band-pass filter. For the BK filter this involves setting the frequency band directly,  $[\phi_{LO}, \phi_{HI}]$  and the number of lead/lags

<sup>14</sup>Details can be found in Hodrick and Prescott (1997) and Baxter and King (1999).

to use in the approximation,  $k$ .<sup>15</sup> In either case, the goal is to recover the business cycle which is typically defined as frequencies of 6-32 quarters. Following Baxter and King (1999) and Ravn and Uhlig (2002) the tuning parameters are set to the optimum values for quarterly data under standard assumptions;  $\lambda = 1600$  in the HP filter and  $\{\phi_{LO}, \phi_{HI}, k\} = \{6, 32, 12\}$  in the BK filter. Although filters are used extensively in the literature, they differ in several aspects. First, they differ in their end point properties. As our sample ends just after the 2008 financial crisis, these end point problems can be particularly severe. Second, they differ in how they react to aggregation. To be precise, let  $y_t$  denote log output,  $\ell_t$  denote labor log input, and  $x_t = y_t - \ell_t$  denote log labor productivity. Then we have that  $HP(x_t) = HP(y_t - \ell_t) = HP(y_t) - HP(\ell_t)$ , however the same does not hold for the BK filter. Consequently we may obtain significantly different results when we look at the correlations with labor productivity.<sup>16</sup>

In practice, researchers account for the structural break in the early 1980s by splitting the sample, filtering on each subperiod, and calculating the relevant statistic. We then take the difference between the two subperiods as the evidence for the structural change.<sup>17</sup> The break date is the onset of the Great Moderation as calculated in, e.g. McConnell and Perez-Quiros (2000) or Stock and Watson (2005). We estimate an American break date of 1983q4 which compares favorably with 1983q2 in Stock and Watson (2005) and 1984q1 in McConnell and Perez-Quiros (2000). We also calculate the break date for all countries in our sample, details of which can be found in section 3.4.1.

Table 3.2 contains the standard deviations and correlations for HP and BK filtered data. The results are consistent with the stylized facts. The standard deviation of GDP and hours declines, as does the correlation between productivity and GDP and productivity and hours. The results are similar between the two methods.

The difference between the two subperiods provides a single summary statistic.

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<sup>15</sup>The BK filter is an approximation to an ideal filter. An ideal filter, among other things, requires an infinite series.  $k$  determines the length of the approximating series. For more details, see Baxter and King (1999).

<sup>16</sup>Brügemann, et al. (2010) and Hagedorn and Manovskii (2011) consider the impact of the definition of labor input and filter choice on the stylized facts found in the US. They find that the choice of filter is unimportant in the US, however the definition of labor input significantly changes the results. See the description of the data in section 3.2.1.

<sup>17</sup>See, e.g., Galí and van Rens (2010).

**Table 3.2:** Second Moments of Filtered Data

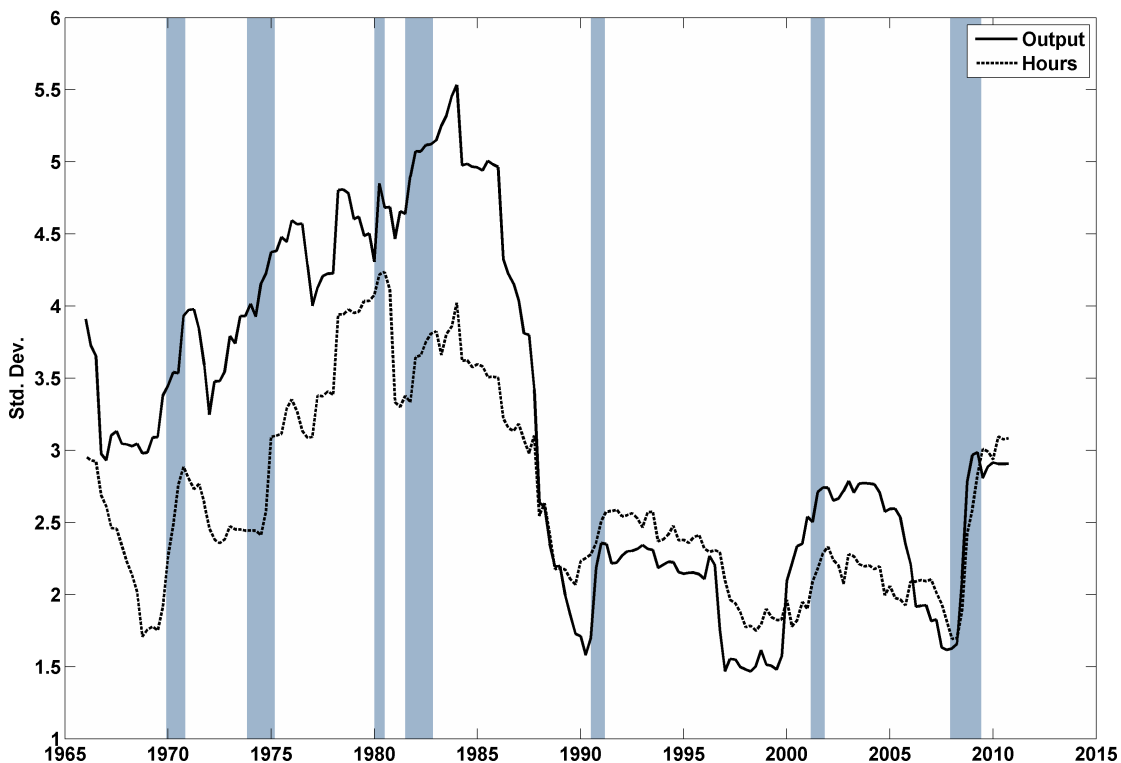
	HP			
	Pre-84	Post-84	Difference	p-value
Std error GDP	7.60	4.38	-3.22	0.00
Std error Hours	6.46	5.23	-1.23	0.02
Std error Productivity	3.68	2.84	-0.84	0.05
Corr(prod, GDP)	0.53	-0.01	-0.54	0.00
Corr(prod, Hours)	0.05	-0.55	-0.60	0.00
	BK			
	Pre-84	Post-84	Difference	p-value
Std error GDP	7.29	3.74	-3.55	0.00
Std error Hours	6.37	4.43	-1.94	0.00
Std error Productivity	3.26	2.27	-0.99	0.01
Corr(prod, GDP)	0.49	-0.03	-0.52	0.00
Corr(prod, Hours)	0.05	-0.54	-0.59	0.00

However, the dynamics of these moments are also of interest, especially mean reversion and break speed. Six-year rolling windows can give us a sense of these dynamics. The results appear in figures 3.1 and 3.2. Volatility of GDP and hours both decline dramatically in the mid-1980s and remain subdued. Even in the recent recession the GDP volatility does not ascend to the heights reached in the 1960s. The volatility of hours, however, returns to levels not seen since prior to the hyperinflation in the 1970s.

The correlations also decline in the mid-1980s, however the procyclicality between productivity and GDP steadily increases after the initial decline. This suggests a more nuanced story than the typical narrative based on simple two period correlations. We see here that the decline in correlation was temporary and actually increased over most of the second half of the sample.

### 3.2.3 (den Haan) VAR forecasting errors

In section 3.2.2 we examined the volatility and correlations without imposing any structure on the data beyond a single structural break. Here we impose the minimal multivariate structure of an (non-structural) VAR. However, it is still a time-invariant VAR and so we retain the single break assumption. One drawback is that this method can only examine the correlations, therefore we do not have volatility estimates. In sections



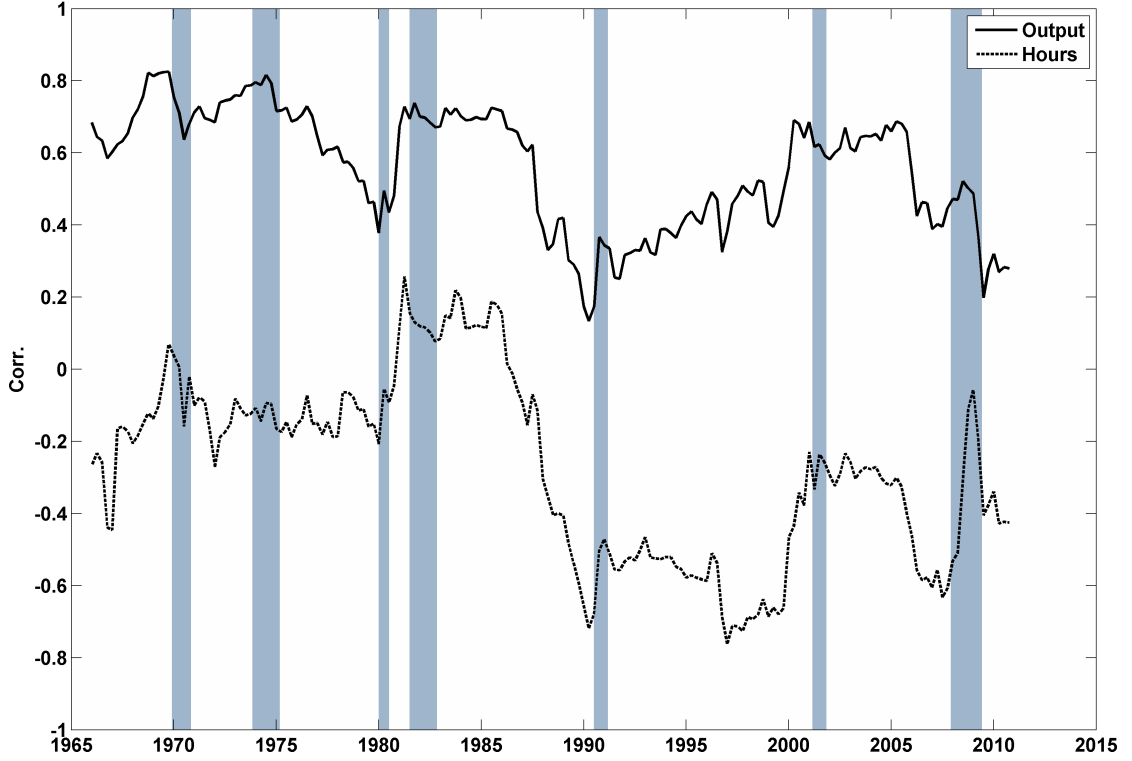
**Figure 3.1:** Annualized US Quarterly Output and Hours Growth: 6-year rolling window

3.2.4 and 3.2.5 we relax the single break assumption and regain volatility measures by estimating two continuous volatility techniques: GARCH and TVP-VAR.

Using VAR forecasting errors to consider the comovement of multiple time series was introduced by den Haan (2000). den Haan (2000) was motivated by the disagreement over empirical results stemming from the use of a single unconditional correlation. This single correlation can be very sensitive to the methods used to calculate it. Instead he proposed the use of calculating the correlation of VAR forecasting errors calculated over a set of horizons. This provides information on the dynamics of the correlation structure that is lost when considering a single summary statistic.

To fix ideas, assume we are interested in the comovement of  $y_t$  and  $x_t$ . Let  $Z_t$  be an  $N$ -vector of endogenous regressors, which includes at least  $y_t$  and  $x_t$ , and consider the following VAR:

$$Z_t = \mu_t + Bt + Ct^2 + \sum_{j=1}^L A_j Z_{t-j} + \epsilon_t \quad (3.1)$$



**Figure 3.2:** US Quarterly Productivity Correlation: 6-year rolling window

where  $A_j$  is an  $N \times N$  matrix of regression coefficients,  $\mu$ ,  $B$ , and  $C$  are  $N$ -vectors of constants, and  $\epsilon_t$  is an  $N$ -vector of innovations, and the total number of lags is equal to  $L$ . Denote the  $K$ -period forecast errors as  $y_{t+K}^{ue}$  and  $x_{t+K}^{ue}$ . Then we are interested in the covariance between these two errors,  $\text{COV}(K)$ .

The components of  $Z_t$  can be any combination of stationary and arbitrarily integrated time series. den Haan shows that  $\text{COV}(K)$  will be consistently estimated, for fixed  $K$ , even if  $Z_t$  is not stationary. This is true so long as (3.1) is well-specified. In particular, if it contains sufficient lags to ensure  $\epsilon_t$  is not integrated.

In addition the forecast error covariances can be considered consistent estimates of the covariances implied by the true impulse-response functions. To see this, rewrite the  $K$ -period forecast error as the sum of forecast updates:

$$y_{t+K,t}^{ue} = (y_{t+K} - E_{t+K-1}y_{t+K}) + (E_{t+K-1}y_{t+K} - E_{t+K-2}y_{t+K}) \\ + \dots + (E_{t+1}y_{t+K} - E_t y_{t+K})$$

Denote the covariance between the  $k$ th terms as:

$$COV^\Delta(k) = COV[(E_{t+K-k+1}y_{t+K} - E_{t+K-k}y_{t+K}), (E_{t+K-k+1}x_{t+K} - E_{t+K-k}x_{t+K})]$$

then, since the forecast errors are serially uncorrelated, there is a simple relationship between  $COV^\Delta(k)$  and  $COV(K)$ .

$$COV(K) = \sum_{k=1}^K COV^\Delta(k)$$

den Haan then shows that  $COV^\Delta(k)$  is equal to the sum-product across all the fundamental shocks of the impulse-responses after  $k$  periods of the underlying series of interest. In other words, assume there are  $M$  fundamental shocks and let  $y_k^{imp,m}$  denote the response after  $k$  periods to a one standard deviation change to the  $m$ th fundamental shock. Then we have

$$COV^\Delta(k) = \sum_{m=1}^M y_k^{imp,m} x_k^{imp,m} \quad (3.2)$$

For  $M = 1$ ,  $COV^\Delta(k)$  is exactly equal to the product of the impulse responses. For  $M > 1$ , first note that the average absolute value is a good estimate of the standard deviation. Then equation (3.2) implies  $COV^\Delta(k)$  measures the comovement after  $k$  periods where each model's fundamental shocks are set equal to its mean absolute value. Therefore  $COV(K)$  measures the cumulative impact of these average impulse-responses.

Why is this important? A popular strategy to estimate DSGE models is to match the impulse-responses from an identified structural VAR and the analogous objects in the DSGE.<sup>18</sup> Those impulse-responses then characterize our object,  $COV^\Delta(k)$ , however they are subject to strict identifying restrictions. Instead, we obtain a consistent estimate of  $COV^\Delta(k)$  directly under minimal assumptions.  $COV^\Delta(k)$  then imposes restrictions on the impulse-response dynamics even though the impulse-responses themselves are unobserved and, indeed, unidentified.

<sup>18</sup>See, e.g. Christiano, Eichenbaum, and Evans (2005)



This is especially important here given the criticisms by Fernald (2007) and Francis and Ramey (2009) of the long-run restrictions for identification introduced in Galí (1999).<sup>19</sup> More generally this addresses the criticism of VAR analyses brought by Benati and Surico (2009). They criticize the lack of connection between structural VARs and the underlying theoretical models. Here we bypass those identifying assumptions by consistently estimating a moment of the impulse-responses, although it yields weaker conclusions.

Figures 3.3 and 3.4 show the results for the US. The figures depict the correlations between productivity and GDP, and productivity and hours, respectively. The VAR lag length is determined by BIC for each country. The correlations are for horizons from 1 to 32 quarters, with 6 to 32 quarters considered the business cycle. Finally three separate estimates are depicted for each correlation, i) the full sample, ii) prior to the volatility break in 1984 and iii) after 1984. For both GDP and hours we see the correlations decline uniformly in the post-1984 period. Further for GDP the correlations are generally less than zero at business cycle horizons, and are all below zero for hours. This matches results found using separately filtered data for GDP and the volatility accounting procedure for hours in Stiroh (2009).

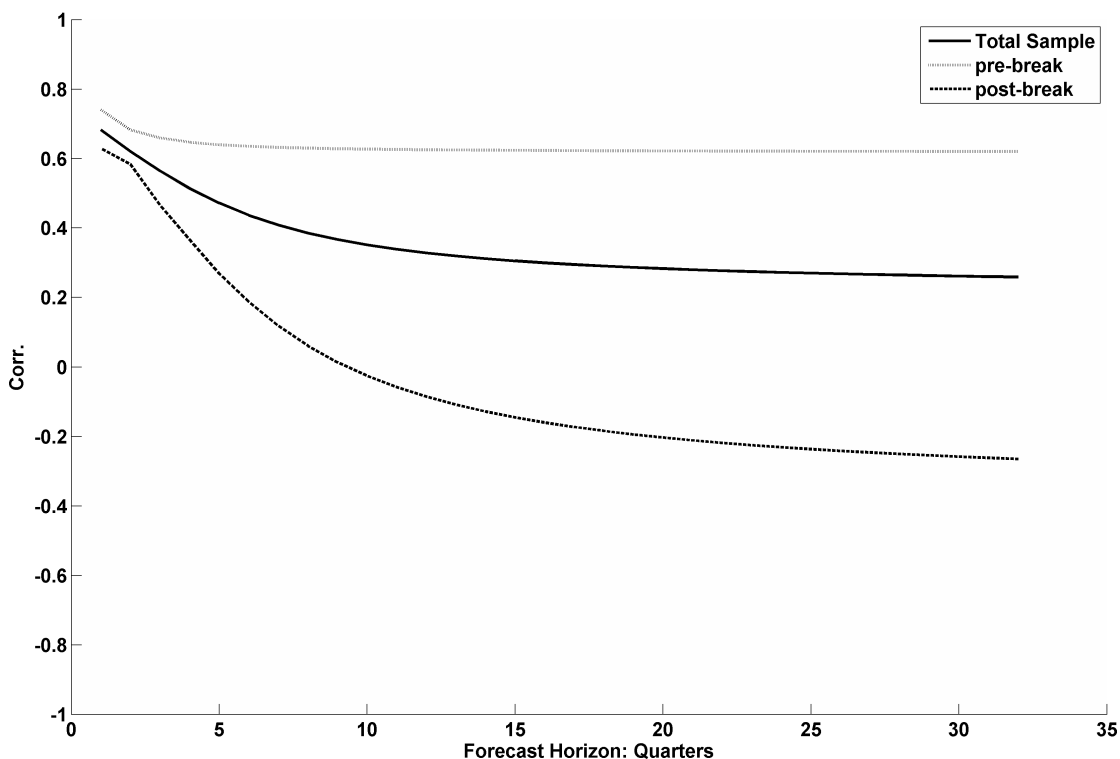
### 3.2.4 Multivariate GARCH

Next we consider explicitly modeling the time-varying volatilities and correlations. This relaxes the single break point assumption made in the previous sections while retaining an explicit multivariate structure. We gain power and efficiency by eliminating the problematic first-stage structural break tests<sup>20</sup> and using the entire sample period. There are two approaches, GARCH and stochastic volatility models. Here we consider GARCH models and in the following section present a stochastic volatility model.

The unconstrained multivariate GARCH model is too complicated to bring to data. There exist a number of simplifying parameterizations that involve restricting the off-diagonal elements of the covariance matrix or the autoregressive structure. For

<sup>19</sup>These restrictions are used in section 3.2.5 in the time-varying parameter VAR of Galí and Gambetti (2009).

<sup>20</sup>See the discussion in section 3.2. Also Cogley and Sargent (2005) and Benati (2007).

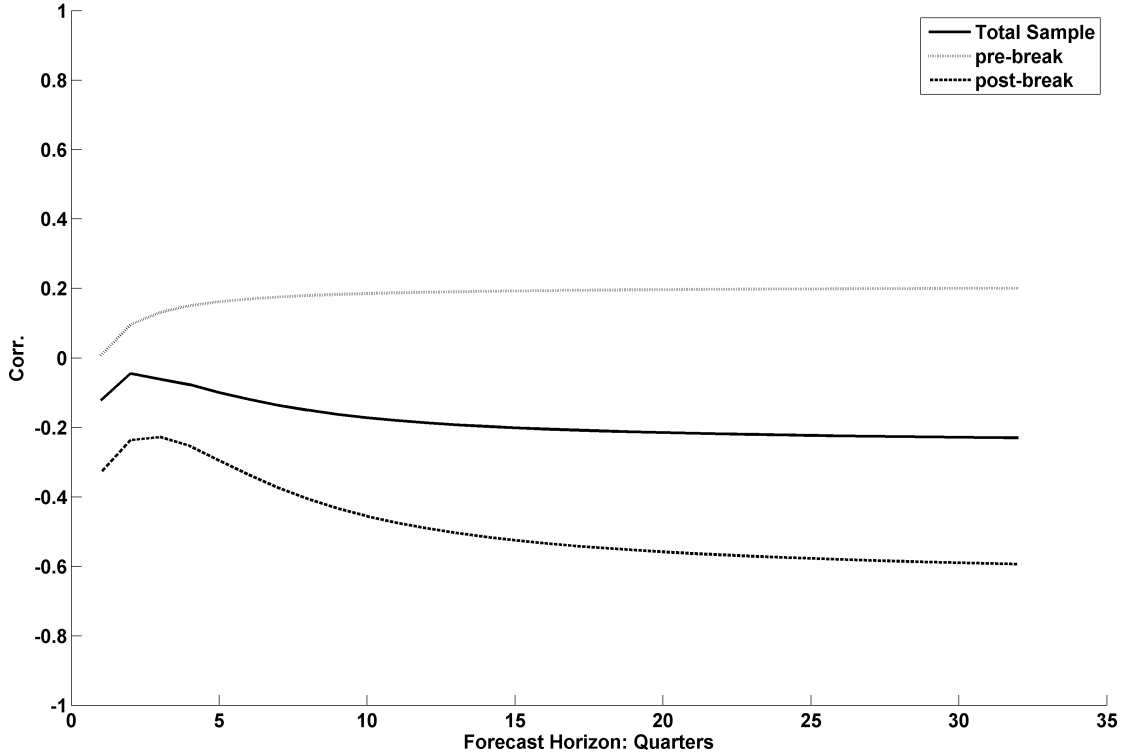


**Figure 3.3:** den Haan VAR forecast correlation: US hourly productivity and output

instance, Bollerslev *et al.* (1988) use the vec operator to eliminate cross-terms from the ARCH specification. However this had difficulty ensuring positive definiteness of the covariance matrix. The BEKK model of Engle and Kroner (1995) provides sufficient conditions on the VEC model parameters to ensure positive definiteness. Reducing the dimension can be accomplished by assuming a factor structure, leading to the F-GARCH specification of Engle *et al.* (1992), but this is just a special case of the BEKK model. For a recent survey of the many methods and their complications, see Bauwens *et al.* (2006).

Here we implement the Engle (2002) dynamic conditional correlation (DCC-) GARCH model.<sup>21</sup> This has two appealing features. First, it is a two step procedure whereby we first estimate separate univariate GARCH models and then, taking those parameters as given, estimate the correlation structure. This estimation is simpler than fully multivariate GARCH and avoids those models' difficulties with convergence and

<sup>21</sup>An alternative model with similar flexibility is the Varying Conditional Correlation (VCC-) GARCH model of Tse and Tsui (2002).



**Figure 3.4:** den Haan VAR forecast correlation: US hourly productivity and hours

strong assumptions required to ensure positive definiteness. Second, this fits neatly into our investigative paradigm. We are interested in both the time-series of the volatilities for each series as well as their comovement. This procedure returns the volatilities as an intermediate output in the first step. Anticipating our conclusion, it also provides a simple extensible framework to consider a larger space of structural mechanisms for the Great Moderation.

Following the notation in Engle (2002) the model is given by:

$$\begin{aligned}
 \nu_{t|t-1} &\sim N(0, D_t R_t D_t) \\
 D_t^2 &= \text{diag}\{\omega_i\} + \text{diag}\{\kappa_i\} \circ \nu_{t-1} \nu_{t-1}' + \text{diag}\{\lambda_i\} \circ D_{t-1}^2 \\
 \epsilon_t &= D_t^{-1} \nu_t \\
 Q_t &= S \circ (\iota \iota' - A - B) + A \circ \epsilon_{t-1} \epsilon_{t-1}' + B \circ Q_{t-1} \\
 R_t &= \text{diag}\{Q_t\}^{-1/2} Q_t \text{diag}\{Q_t\}^{-1/2}
 \end{aligned}$$

where  $\circ$  is the Hadamard product,  $\nu_t$  is a zero-mean residual,  $D_t$  is the diagonal volatility matrix,  $R_t$  is the correlation matrix, and  $S$  is the unconditional covariance of the epsilons. The normality assumption ensures to a likelihood function which can be maximized directly. However, Engle (2002) provides a simpler two-step estimator that is consistent but inefficient. This proceeds by decomposing the log-likelihood into two parts, one that governs the volatility and another for correlation. Let  $\theta$  denote the volatility parameters and  $\phi$  denote the correlation parameters. Then we have

$$\begin{aligned} L(\theta, \phi) &= L_V(\theta) + L_C(\theta, \phi) \\ L_V(\theta) &= -\frac{1}{2} \sum_t (n \log(2\pi) + \log |D_t|^2 + \nu_t' D_t^{-2} \nu_t) \\ L_C(\theta, \phi) &= -\frac{1}{2} \sum_t (\log |R_t| + \epsilon_t' R_t^{-1} \epsilon_t - \epsilon_t' \epsilon_t) \end{aligned}$$

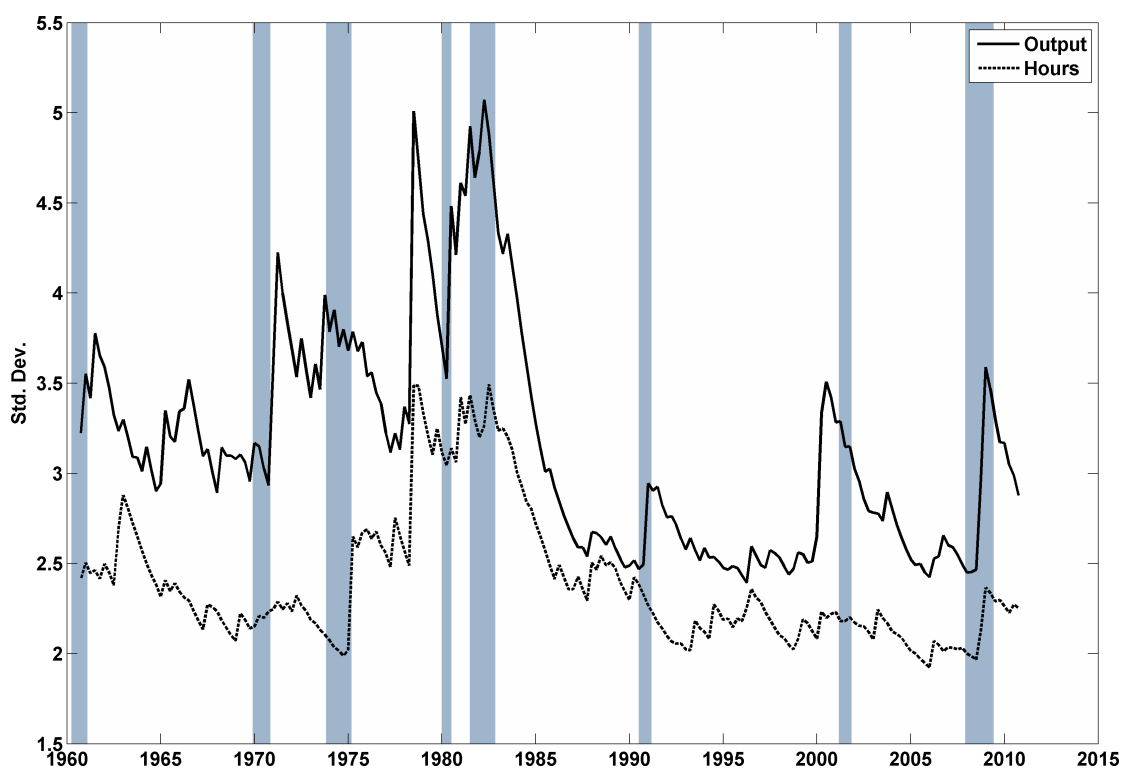
It turns out that  $L_V(\theta)$  is the log-likelihood of the sum of univariate GARCH likelihoods, which is optimized by maximizing each term separately. This can be done with standard software routines.<sup>22</sup> When we have a consistent estimator for these GARCH models (as we do here), denoted by  $\hat{\theta}$ , then we can substitute that into  $L_C(\hat{\theta}, \phi)$  to obtain a consistent estimator for  $\phi$ .

Our conditional mean model is a VAR in GDP and hours growth with two lags. Since GDP and hours are measured in logs, productivity is a linear combination of GDP and hours. Thus, the correlations with productivity are calculated as linear combinations of the variances and covariances of GDP and hours. See appendix G. The univariate errors from the first stage estimation are modeled as GARCH(1,1) processes.<sup>23</sup> Figure 3.5 shows the results for GDP and hours. Reassuringly, the figure corresponds closely with the rolling window figures from section 3.2.2, albeit much less smooth. The stark decline in volatility in the mid-1980s is readily apparent, as is the subsequent extended period of calm. There are isolated spikes in GDP volatility but it largely remains below

<sup>22</sup>We use Kevin Shepherd's Oxford MFE toolbox for Matlab. This is a significant rewrite of his earlier UCSD\_GARCH toolbox. [http://www.kevinsheppard.com/wiki/MFE\\_Toolbox](http://www.kevinsheppard.com/wiki/MFE_Toolbox)

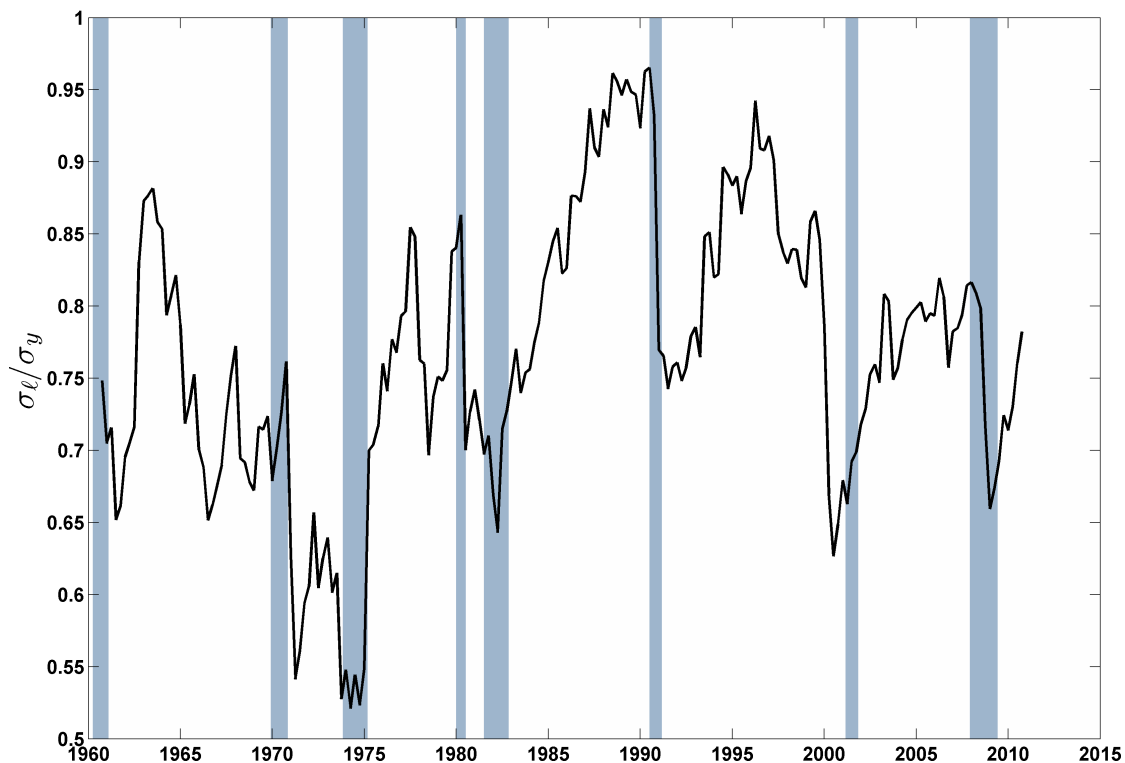
<sup>23</sup>The qualitative results were unchanged for other GARCH(p,q) processes and excluding the exogenous regressors. The adequacy of GARCH(1,1) specifications, absent leverage effects, can be found in, e.g., Hansen and Lunde (2005).

the levels seen in the 1970s. Hours, as with the rolling windows, returns to the subdued levels before the 1970s. Figure 3.6 depicts the volatility of hours relative to output. The relative volatility of hours is higher, on average, in the post-84 period although with frequent sharp drops coinciding roughly with recessions. Looking at the previous two figures we see that these declines are generated by transient output volatility spikes.



**Figure 3.5:** Annualized US quarterly growth volatility: GARCH(1,1)

The volatility results are all obtained using standard GARCH methods. We now turn to the conditional correlation estimates. Figure 3.7 depicts the correlation between labor productivity and both output and hours. First note the correlation between productivity and hours declines in the mid-1980s and then recovers during the 2000s. This mimics the rolling window results although the decline is not as stark. Interestingly, the GARCH estimates of the correlation between labor productivity and output *rise* over this time period. This is the first example of a discrepancy between the estimation methods, and corresponds with perhaps the most important moment we consider. Recall the decline in the procyclicality of labor productivity is given as *a priori* evidence against the RBC model. This suggests that empirical fact is sensitive to estimation method. Further



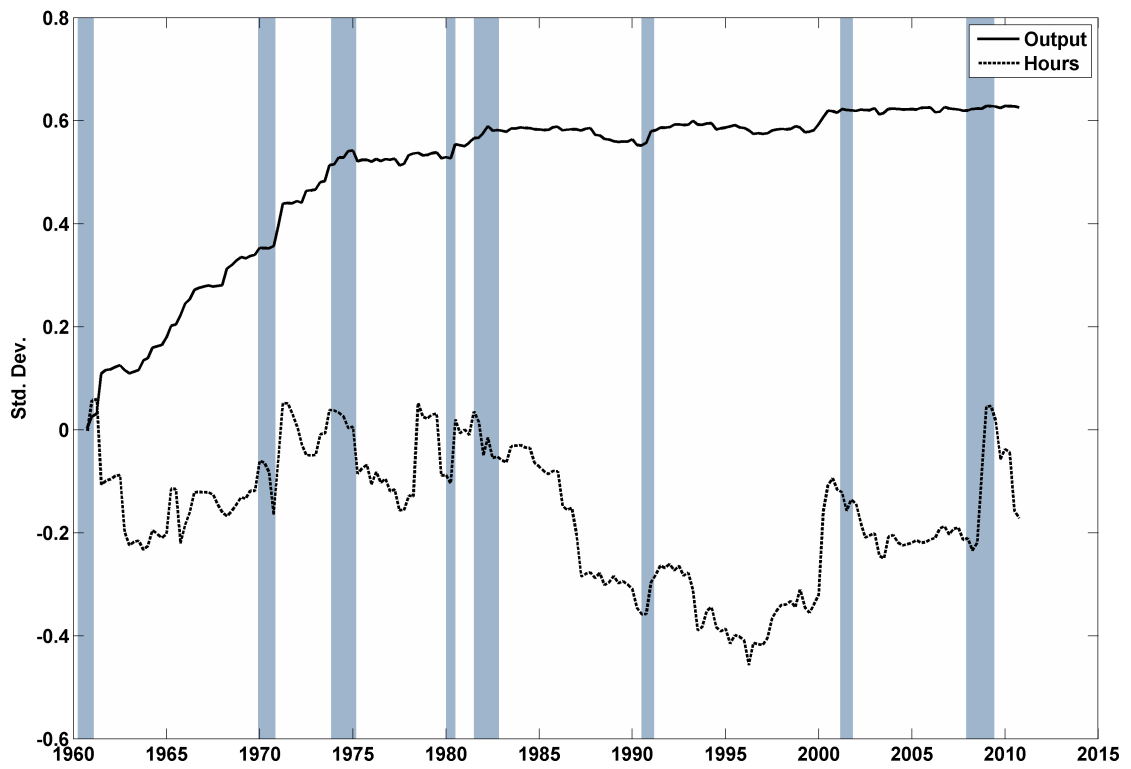
**Figure 3.6:** Ratio of US labor input volatility to output volatility: Individual GARCH(1,1)

evidence for the sensitivity of correlation estimates is found in the next section where we find similar results for the TVP-VAR model.

### 3.2.5 Time-Varying Parameter VAR

Our final model considers stochastic volatility, an alternative to GARCH for modeling time-varying volatility. It also adds a final innovation, time-varying conditional means via the time-varying coefficients. Both features are necessary in a TVP-VAR due to the model's flexibility. If one feature is missing, then the other will compensate in order to match the time variation found in the data, thereby biasing the estimates.<sup>24</sup> Given the model's complexity, we separate the technical discussion and empirical results into the following two subsections.

<sup>24</sup>See the discussion in Cogley and Sargent (2005) and Stock (2002).



**Figure 3.7:** Correlation with US labor productivity: DCC-GARCH

### 3.2.5.1 Model

We use the time-varying parameter VAR model found in Galí and Gambetti (2009), which incorporates elements of Primiceri (2005) and Cogley and Sargent (2005). The VAR model is given by

$$z_t = c_t + B_{1,t}z_{t-1} + \dots + B_{k,t}z_{t-k} + u_t \quad t = 1, \dots, T \quad (3.3)$$

where  $z_t$  is an  $n \times 1$  vector of observed endogenous variables;  $c_t$  is an  $n \times 1$  vector of time varying coefficients that multiply constant terms;  $B_{j,t}$ ,  $j = 1, \dots, k$ , are  $n \times n$  matrices of time varying coefficients;  $u_t$  are heteroscedastic unobservable shocks with variance covariance matrix  $\Omega_t$ . We assume that the roots of the VAR polynomial lie outside the unit circle for all  $t$ .

Further, consider the triangular decomposition of  $\Omega_t$

$$A_t \Omega_t A_t' = \Sigma_t \Sigma_t'$$

where  $A_t$  is the lower triangular matrix

$$A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n1,t} & \cdots & \alpha_{n(n-1),t} & 1 \end{bmatrix}$$

and  $\Sigma_t$  is the diagonal matrix

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix}$$

Thus we model the time-varying volatility and covariances separately.



Stacking in a vector  $\theta_t$  all the R.H.S. coefficients, (3.3) can be rewritten as

$$\begin{aligned} z_t &= G'_t \theta_t + A_t^{-1} \Sigma_t \epsilon_t \\ G'_t &= I_n \otimes [1, z'_{t-1}, \dots, z'_{t-k}] \end{aligned} \quad (3.4)$$

where the symbol  $\otimes$  denotes the Kronecker product, and  $V(\epsilon_t) = I_n$ .

Let  $\alpha_t$  be the  $[n \times (n - 1)]/2$  vector of non-zero and non-one elements of the matrix  $A_t$  stacked by row and  $\sigma_t$  be the vector of the diagonal elements of the matrix  $\Sigma_t$ . The dynamics of the time varying parameters is then given by

$$\begin{aligned} \theta_t &= \theta_{t-1} + \nu_t \\ \alpha_t &= \alpha_{t-1} + \zeta_t \\ \log \sigma_t &= \log \sigma_{t-1} + \eta_t \end{aligned} \quad (3.5)$$

where all the innovations are assumed to be jointly normally distributed. The variance covariance matrix,  $V$ , is assumed to have the following block diagonal form

$$V = \text{Var} \left( \begin{bmatrix} \epsilon_t \\ \nu_t \\ \zeta_t \\ \eta_t \end{bmatrix} \right) = \begin{bmatrix} I_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}$$

where  $I_n$  is an  $n$ -dimensional identity matrix;  $Q$ ,  $S$ , and  $W$  are positive definite matrices. Additionally, we will assume that  $W$  is diagonal and  $S$  is block diagonal with the blocks corresponding to the parameters from separate equations.

The model is cast as a set of state-space models following Primiceri (2005). In general, each state-space model is a simple transformation of the measurement and state equations given by equations 3.4 and 3.5, respectively. Each model is then estimated using a Bayesian state-space Gibbs sampling algorithm developed in Carter and Kohn (1994). Details of the prior specifications and estimation algorithm are found in the appendix. Briefly, the Gibbs sampler allows us to sample from the joint distribution by iteratively sampling from a set of conditional distributions. The gain comes from

converting an intractable high dimensional joint distribution into a series of much simpler conditional distributions. After a sufficient number of initial iterations (the burn-in period), the draws will be from the true joint distribution. Our estimates are the corresponding sample moments from a series of draws from this joint distribution.

### 3.2.5.2 US Results Discussion

The VAR is in the growth of productivity and hours, in logs, with two lags. This matches the specification found in Galí and Gambetti (2009). The volatility of and correlation with GDP is calculated using the linearity of productivity induced by the log specification. See appendix G. Figures 3.8 and 3.9 depict the US results for volatility and correlation, respectively. These results compare favorably with Galí and Gambetti (2009), although we have a longer time series and consider the whole economy rather than the non-farm business sector.<sup>25</sup> The volatility of GDP and hours decline precipitously in the early 1980s while labor productivity declines steadily over the sample. Also note that the volatility of hours declines more and remains below the pre-1970s level, unlike our previous results. However we lose much of the 1960s in order to center the prior and thus do not have a long pre-peak sample to compare against.

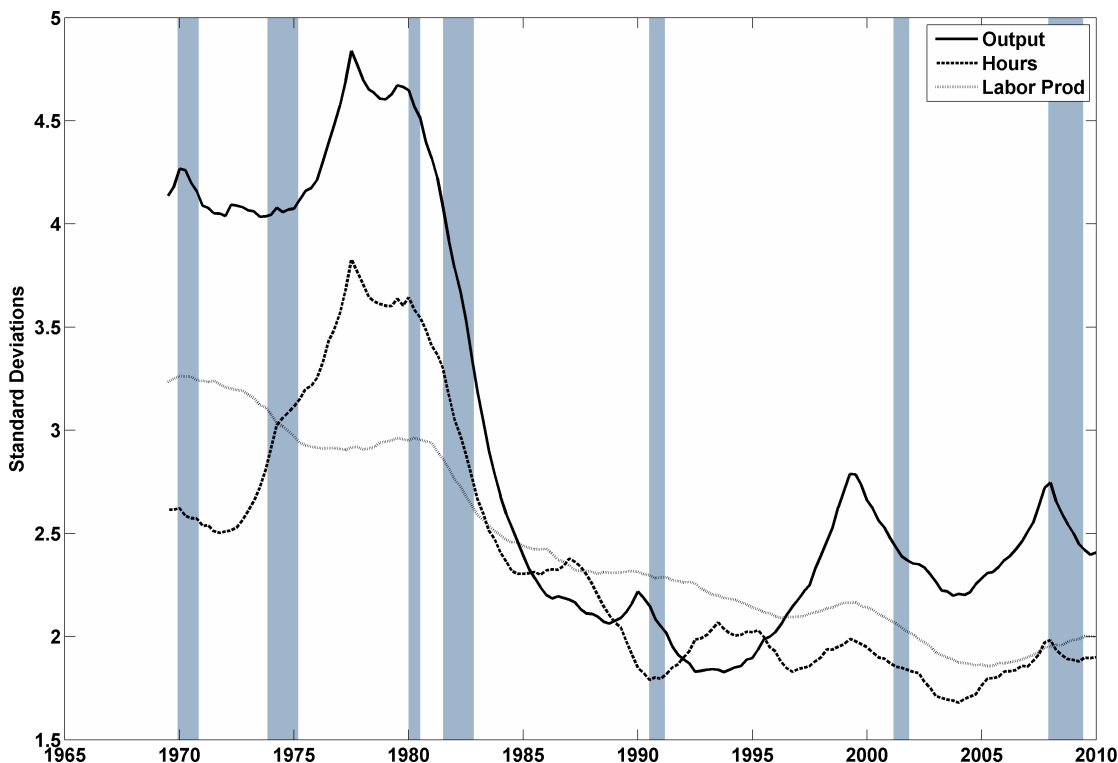
The decline in correlation between productivity and hours coincides with output in the early 1980s as we have found previously. Notice, however, the correlation between productivity and output declines until the late 1980s and then subsequently increases. It also does not decline as much as with the previous techniques. It clearly remains procyclical. This matches the results found in Galí and Gambetti (2009). However in a subsequent paper, Galí and van Rens (2010) ignore the TVP-VAR results and use the univariate filter results to justify their theoretical model instead.

### 3.2.6 Summary of US Results

This section seeks to confirm the US stylized facts found in the literature using our data set and ascertain their sensitivity to statistical method. We consider both continuous volatility measures and multivariate conditional means. We find that all the stylized

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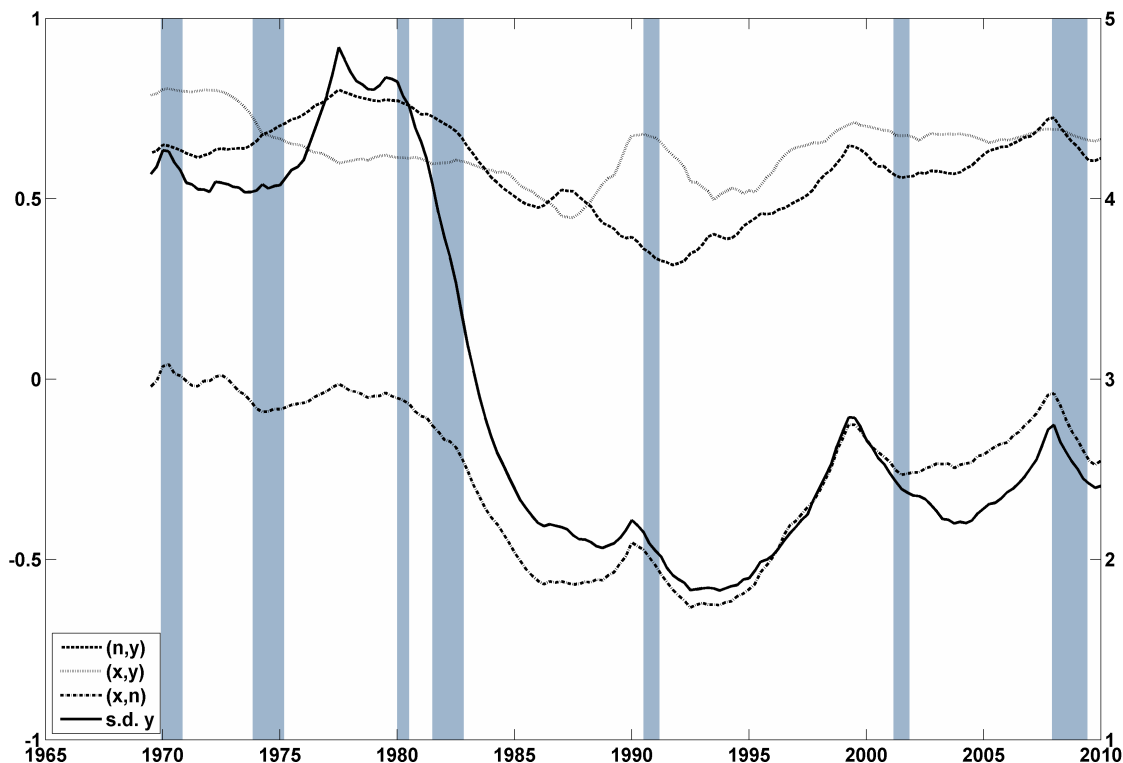
<sup>25</sup>These correspond to figures 1a and 2 from Galí and Gambetti (2009). They use proprietary data from the Haver USECON database (see their footnote 10).



**Figure 3.8:** US conditional volatility: TVP-VAR

facts are robust to how we model the non-stationarity except for the correlation between labor productivity and output. The two continuous measures, DCC-GARCH and TVP-VAR, provide estimates that do not support labor productivity becoming acyclic. This contradicts the received wisdom that the cyclicity of productivity has declined and diminished the usefulness of RBC models. However, it is unclear whether the moments matched in calibration exercises are the objects of interest. Alternative statistical specifications may provide a better fit to the procyclicality of labor productivity while leaving the other (already well fit) moments unchanged.<sup>26</sup> The next section compares international data to the US experience. Given these results, the correspondence with the US on the correlation of labor productivity and output must be treated with some skepticism.

<sup>26</sup>See Morris (2011) for a discussion of this and related issues in the context of calibration. In addition, higher order approximations and other moment restrictions have recently been shown to have first order effects in DSGE models. He also provides an alternative estimation methodology that overcomes these issues.



**Figure 3.9:** US unconditional correlation: TVP-VAR

### 3.3 Labor Market Frictions Model

The model of Galí and van Rens (2010) can generate all of the macro-moment stylized facts via a decline in labor market frictions. This section sketches the intuition behind their result.

They consider two extremes of fully flexible and completely rigid labor markets. They model this with two labor market frictions; endogenous effort choice and convex labor adjustment costs, i.e. hiring costs. Endogenous effort choice provides an intensive margin that is not subject to the adjustment cost. This provides a labor margin that is able to adjust to shocks in the completely rigid environment. Their two driving shocks are to technology and preferences. In addition, labor adjustment costs generate wage rigidity. This is because existing matches generate a surplus, equal to the adjustment cost, that is split between workers and the firm. Effort is assumed to have a higher marginal disutility and stronger diminishing returns than employment. With no adjustment costs, the intensive margin is never adjusted since it is dominated by employment. With infinite

adjustment costs, only effort is adjusted.

The signs of the correlations depend upon the parameters governing the intertemporal elasticity of consumption, disutility of effort, diminishing returns to total labor, and diminishing returns to effort, as well as the relative size of technology and preference shocks. The primary difference between the regimes is the excess sensitivity to the underlying shocks along the intensive margin. We show in appendix I the inequalities necessary to generate the observed changes in the US. In particular, if technology shocks are sufficiently more volatile than preference shocks then we obtain all of the labor market moments.

The decline in output volatility is generated by a change in the flexibility of wages. More flexible wages are able to counteract technology shocks and reduce output volatility. More flexible wages follow from the smaller surplus, and smaller bargaining set, generated by smaller adjustment costs. While they are able to generate the correct *sign*, their calibrated wage rigidity is too small to generate the observed *magnitude* of decline in output volatility. However, in the US the change in labor market dynamics coincides with the change in output dynamics, as shown in section 3.2.

We do not estimate their DSGE model directly. Instead, we consider the moments it can theoretically generate and then we will compare them to the observed pattern of labor market frictions. Their model is highly stylized and a close correspondence between the structural labor market parameters and data is difficult to achieve. We consider the model under a best-case scenario; it can already generate all of the desired moments and perhaps can generate the US output moments with better data. Therefore, when we compare the international data to the US, we will include the well-documented international change in output volatility among our classifying variables. We stress this is a stronger statement than advocated by Galí and van Rens (2010) but we believe it illustrates how closely the international Great Moderation experience matches the US, and whether their mechanism is capable of delivering the disparate results.

### 3.4 International Results

In section 3.2 we showed that the stylized facts in the US are robust to statistical method with the exception of the correlation between labor productivity and output. Here we extend the analysis to thirteen additional countries. We observe significant heterogeneity across countries. As an organizational framework, we therefore classify the countries according to whether their moments match the US. By organizing the countries according to whether they match the US, in section 3.5 we will be able to examine whether labor market frictions declined in those countries.

To be precise, we classify the countries into three categories: 1) those that agree with the US experience, 2) those that are the exact opposite, and 3) those with mixed results. The first two categories have clear, but opposite, predictions of labor market frictions according to Galí and van Rens (2010); decreasing in the first case and increasing in the latter. For countries with mixed results, there are several possibilities. First, the underlying structural parameters can be significantly different than those found in the US. This suggests consumption preferences, labor preferences, or the returns to labor vary significantly across countries. Second, the shocks themselves may vary across countries. Specifically, the economies have the same response to the shocks however technology shocks are much less volatile than preference shocks. Lastly, the shocks and structural parameters may be the same however a complex time series of labor frictions may generate complex movements in the moments. Our classification thus extracts the cleanest predictions regarding labor market frictions with a minimum of assumptions. This is important since measures of labor market frictions are controversial and relatively coarse.

We emphasize that this is not definitive evidence for or against Galí and van Rens (2010) but rather an indication of the relative importance of their mechanism if we assume countries are similar to the US. Their strong conclusions are supported by implicitly extrapolating the US experience to the rest of the world. Otherwise, their argument rests on the idiosyncratic experience in the US, i.e. data-mining.

### 3.4.1 Output Volatility Break Dates

Recall that two methods, univariate filters and den Haan, require a break date. We estimate the volatility break following Sensier and van Dijk (2004). Let  $W(\tau)$  denote the Heteroskedasticity and Autocorrelation Consistent (HAC) Wald test of the null hypothesis  $H_0 : \delta_1 = \delta_2$  in the regression

$$\sqrt{\frac{\pi}{2}}|y_t - \hat{\mu}| = \delta_1\{1 - I(t > \tau)\} + \delta_2 I(t > \tau) + \epsilon_t, \quad t = 1, \dots, T$$

where  $\hat{\mu}$  is the sample mean,  $T$  is the number of time periods,  $\tau$  is the specified break date, and  $I(\cdot)$  is the indicator function. If we treat  $\tau$  as unknown then we can test for the presence of a break using a variety of statistics: sup-Wald [Andrews (1993)], AveW or ExpW [Andrews and Ploberger (1994)]. Point estimates of the break date are given by the  $\tau$  that minimizes the sum of squared errors in the regression (equivalently, the  $\tau$  in the SupW statistic).

$$SupW = \sup_{\tau_1 < \tau < \tau_2} W(\tau)$$

The middle 70% of the sample is used to estimate the change point. This means that  $\tau_1 = [0.15T]$  and  $\tau_2 = [0.85T]$ , where  $[\cdot]$  denotes the integer part. Approximate asymptotic p-values are obtained using the method of Hansen (1997).

Table 3.3 gives the estimated break dates for hours and GDP as well as the Stock and Watson (2005) results for comparison. Relative to Stock and Watson (2005), we obtain very similar results for output. The hours break date differs from that of output by more than a decade for 5 of the 13 countries, and does not always lead GDP. We also calculate a second break date conditional on the first. This is done primarily for Japan in order to center all the calculations in the Great Moderation narrative time period. However note the second break in GDP is much closer to that of hours for France. The earlier GDP break date is due to the idiosyncratic May 1968 strike that brought France to a standstill and will be readily apparent in the sections to follow. Interestingly Finland's break date is in the early 1980s rather than the early 1990s when its trade collapsed with the Soviet Union and it mismanaged financial market deregulation following a domestic credit crisis [Nickell (1997)]. This confluence of events over the period 1990-1993 saw the unemployment rate more than triple from 3.4% to 17.7%. Unlike France, this period

**Table 3.3:** Break in Volatility for Hours and GDP

	Estimated Break Date			Stock and Watson (2005)
	Hours	GDP (1st)	GDP (2nd)	GDP
Australia	1980q1	1983q3	2005q3	-
Austria	1992q2	1988q2	1972q4	-
Canada	1983q2	1987q1	1966q2	1991q2
Finland	1983q3	1981q1	1992q3	-
France	1979q2	1969q1	1979q1	1968q1
Germany	1970q1	1993q1	1984q2	1993q1
Ireland	1997q3	1996q2	1986q1	-
Italy	1968q2	1980q1	2006q2	1980q1
Japan	1976q1	2003q2	1990q3	$p > 5\%$
Norway	1982q4	1977q4	1998q2	-
Sweden	1990q3	1992q2	2007q4	-
UK	1991q1	1980q4	2006q1	1980q1
US	1984q3	1983q4	1999q4	1983q2

Notes: GDP (1st) and GDP (2nd) correspond to the primary break date and the secondary break date conditional on the first, respectively. Stock and Watson (2005) only estimate break dates for G7 countries.

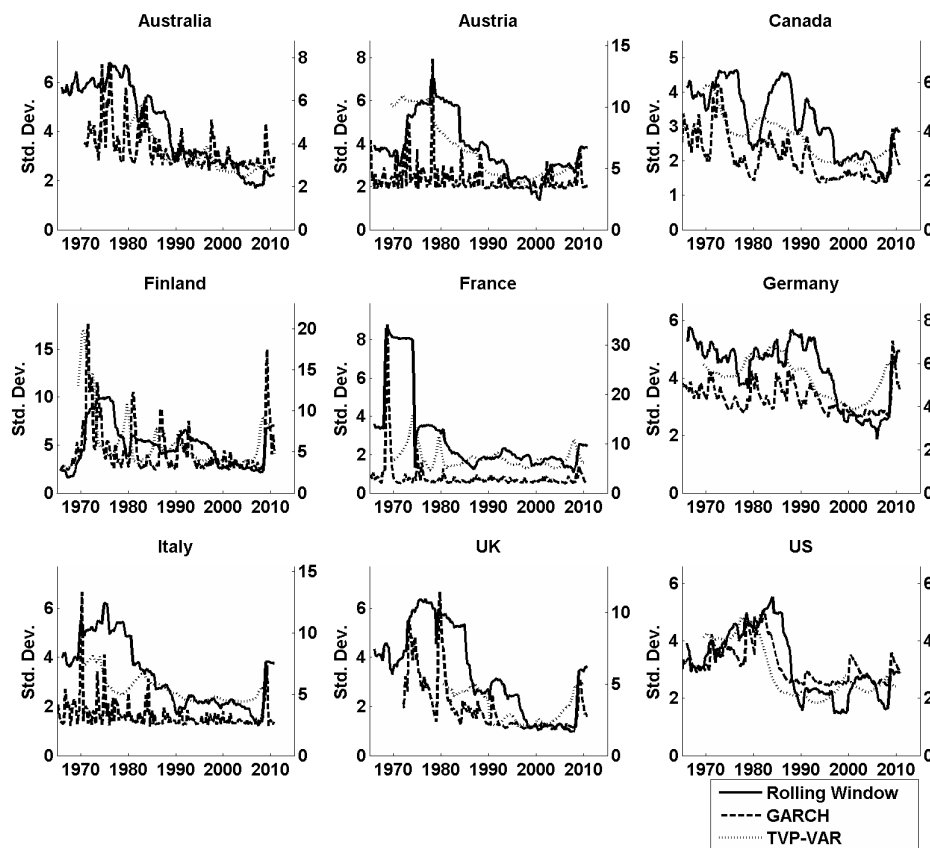
appears as a modest increase in output volatility although we will see an increase in hours volatility in the mid 1980s that presages the crisis to come.

### 3.4.2 Output Volatility

We begin our classification by splitting the countries according to whether output volatility declined. International output volatility has been well documented. For the G7, Stock and Watson (2005) estimate an instantaneous volatility measure. Cecchetti et al. (2006) consider 21 countries using the HP filter and split-sample. Given the problems documented with filters in section 3.2.2 and to economize on space, we omit those results in the following sections. In general, they confirm the continuous results or are insignificant, however they are available upon request. Here we instead extend the evidence to continuous measures.

Figures 3.10 and 3.11 depict output volatility measured using a six-year rolling window, GARCH, and TVP-VAR for decreasing and increasing output volatility countries, respectively. The GARCH results are plotted versus the right axis due to isolated spikes in a few of the countries.



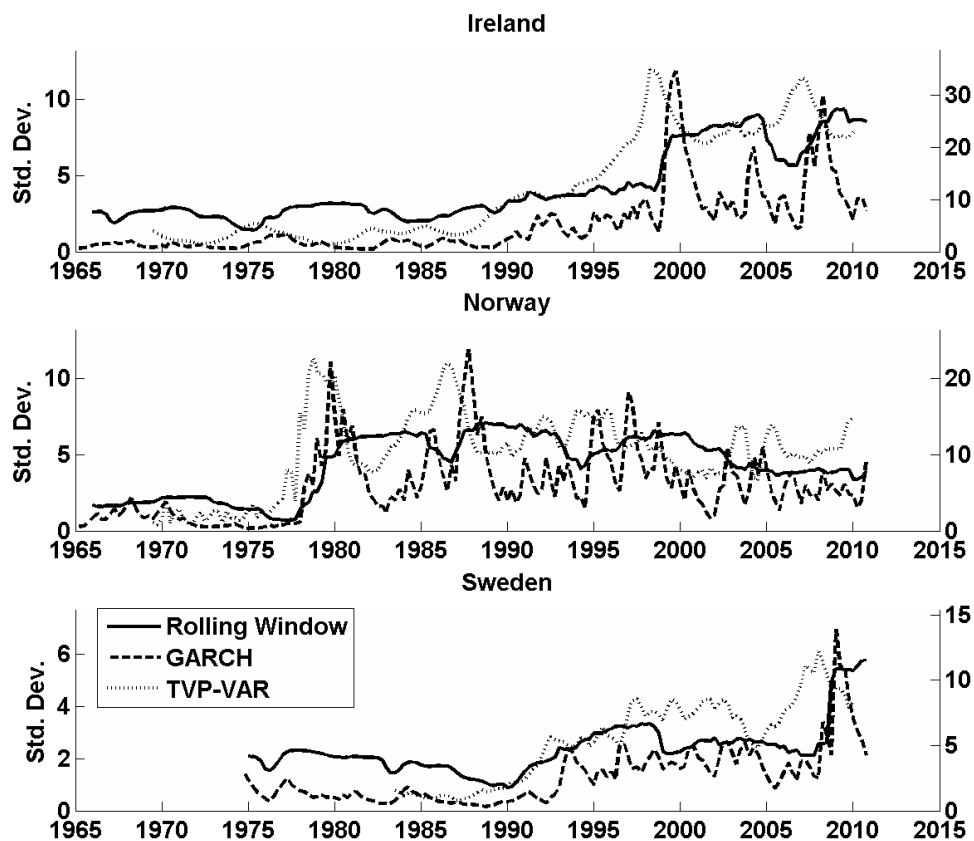


**Figure 3.10:** Decreasing Output Volatility: International Results

Note: The rolling window and TVP-VAR results are on the left axis, and the GARCH results are on the right axis. The rolling window is based upon a six-year window. The standard deviation is in annualized percent.

Figure 3.10 shows those countries in which output volatility declines. First note that the US results are remarkably clean. All three methods show a sudden decrease in volatility in the early- to mid-1980s. However that pattern is not repeated elsewhere. In general, the rolling window and TVP-VAR results are similar. The GARCH results, on the other hand, are either erratic around the trend (Australia, Finland, UK) or trendless with rapidly mean-reverting spikes in volatility (Austria, France, Italy). The change in volatility is generally not sharp but tends to trend down.

Figure 3.11 displays the three countries whose GDP volatility increased; Ireland, Norway, and Sweden. Ireland and Norway exhibit sharp increases in volatility that are near mirror-images to the US, although separated temporally. Ireland increases in the

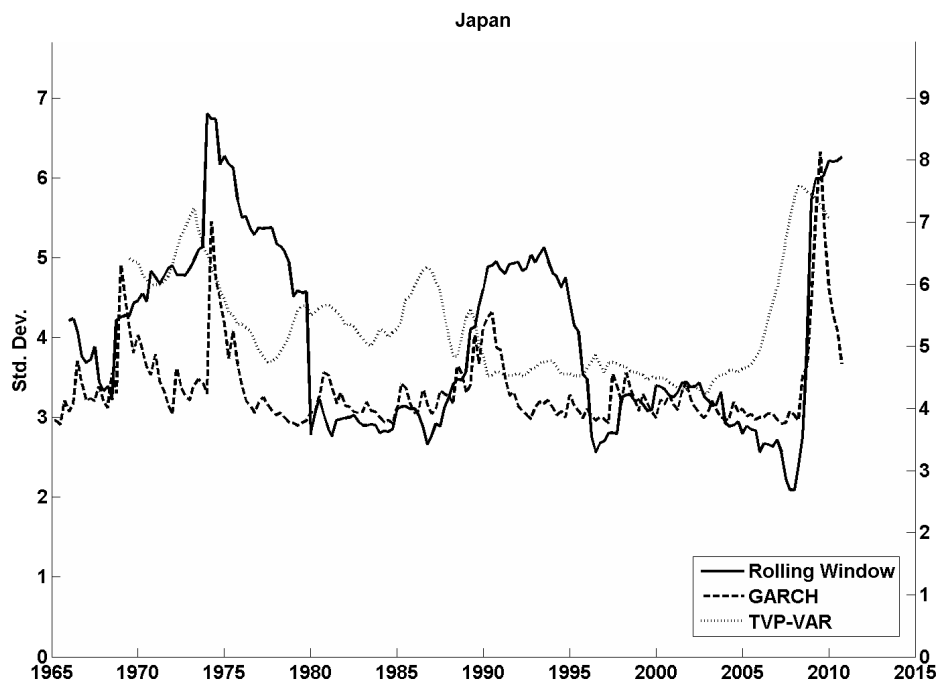


**Figure 3.11:** Increasing Output Volatility: International Results

Note: The rolling window and TVP-VAR results are on the left axis, and the GARCH results are on the right axis. The rolling window is based upon a six-year window. The standard deviation is in annualized percent.

late 1990s well outside the traditional Great Moderation period. Norway, on the other hand, increases in the late 1970s. Sweden's volatility increases more gradually. Note that Sweden's volatility nearly triples over the 1990s decade for all three measures. However the figure is distorted by the tripling again during the recent financial crisis. This brings into sharp relief the impact of the financial crisis. For the countries that already saw an increase in volatility, only Sweden exhibited a further increase during the recent crisis.

The three methods had conflicting results for the final country, Japan, as seen in figure 3.12. According to the rolling window output volatility initially declines and re-



**Figure 3.12:** Neither Increasing nor Decreasing Output Volatility: International Results  
 Note: The rolling window and TVP-VAR results are on the left axis, and the GARCH results are on the right axis. The rolling window is based upon a six-year window. The standard deviation is in annualized percent.

mains stable in the early 1980s, rises and stabilizes at pre-moderation levels for most of the 1990s, and then subsequently declines again. The GARCH results are inconclusive and the TVP-VAR has a roughly downward trend.

For our six new countries, we find that the instantaneous volatility follows a clear trend. This extends the international results found in Cecchetti et al. (2006) and shows that the standard practice of splitting the sample does not obscure any complex dynamics. For the G7, our results are similar to those found in Stock and Watson (2005). They estimate an autoregression with stochastic volatility using a non-Gaussian smoother. This is similar to our TVP-VAR setup. There are three noteworthy differences. First, they find the volatility in France to be relatively constant. France's results are dominated by a series of national strikes in the late 1960s and early 1980s. In particular the May 1968 strike which is the largest strike on record. Rather than remove the outlying

observation, which represents real labor frictions present in the economy, we consider how extreme results may influence the methods under consideration. Second, they find German volatility declines over the entire sample. The series they use has been discontinued but the difference is likely how East and West German data are combined prior to 1993. Lastly, they find Japan's volatility declines until the mid-1980s and then rises monotonically over the later period.<sup>27</sup>

### 3.4.3 Labor Market Stylized Facts

#### 3.4.3.1 Hours Volatility and Relative Volatility

Galí and Gambetti (2009) present empirical evidence for the US that hours volatility decreases but it decreases less than output volatility. Thus the volatility of hours relative to the volatility of output increases.

In order to match the US, the countries where output volatility declined must also have the relative volatility of hours increase. Figure 3.13 shows the results for the countries where this prediction holds. With the exception of Finland and France, we see the ratio increase in all of the countries. In Finland the ratio increases only for the rolling window. The other two methods do not show a clear trend. For France the ratio initially increases but begins decreasing around the final major strikes in the early 1980s, i.e. when output volatility begins settling down. The patterns in these two countries therefore are not consistent with the US.

For the remaining countries, the increase in the ratio can also be due to an increase in the hours volatility. Figure 3.14 examines this possibility. We see that hours volatility increases for Australia, Austria, Finland, Italy, and the UK. Thus the only countries that remain consistent with the US are Canada and Germany.

We now turn to the countries where output volatility increased. Here we expect the relative volatility to decrease and hours volatility to increase. Figure 3.15 shows that the relative volatility decreases for all these countries. Figure 3.16 confirms that this is not due to hours volatility decreasing.

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<sup>27</sup>These are also similar to G7 results found in Blanchard and Simon (2001).

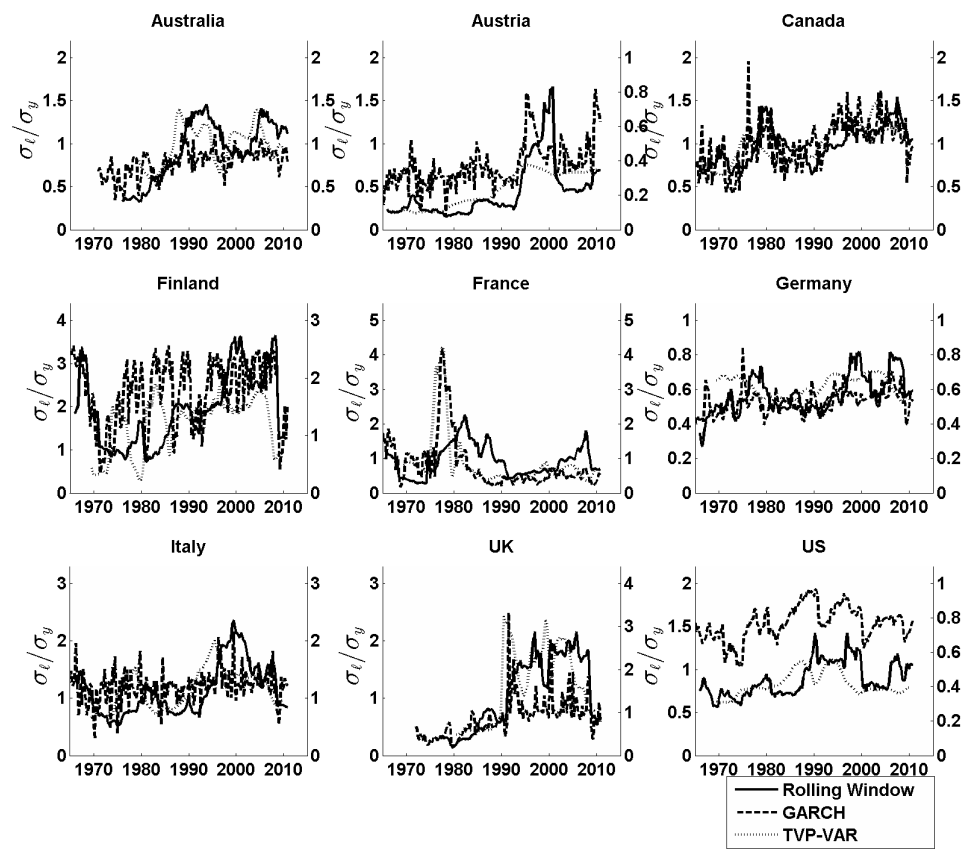


Figure 3.13: Volatility of Hours Relative to Output: Predicted Increase

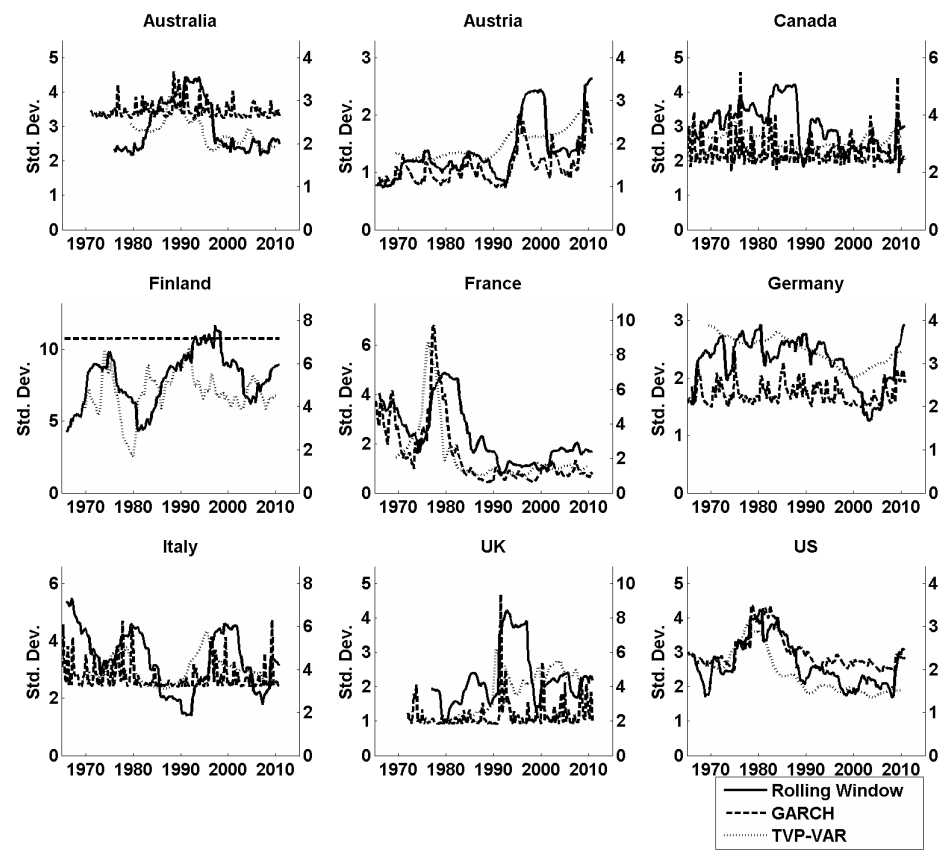
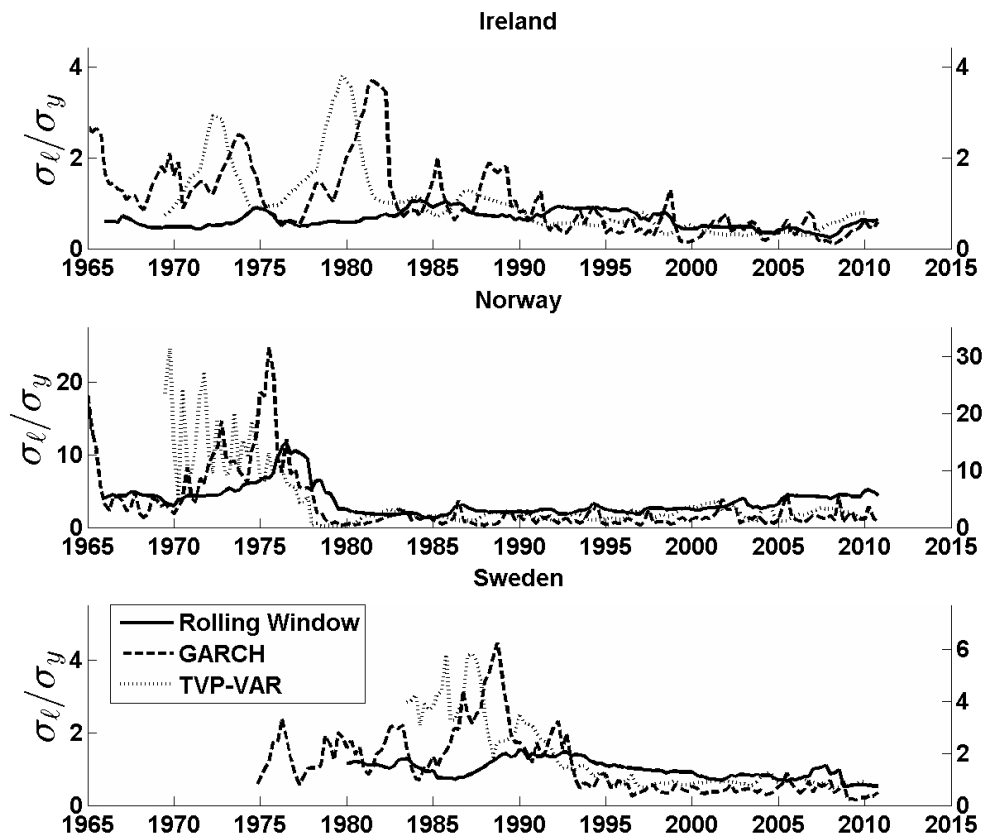
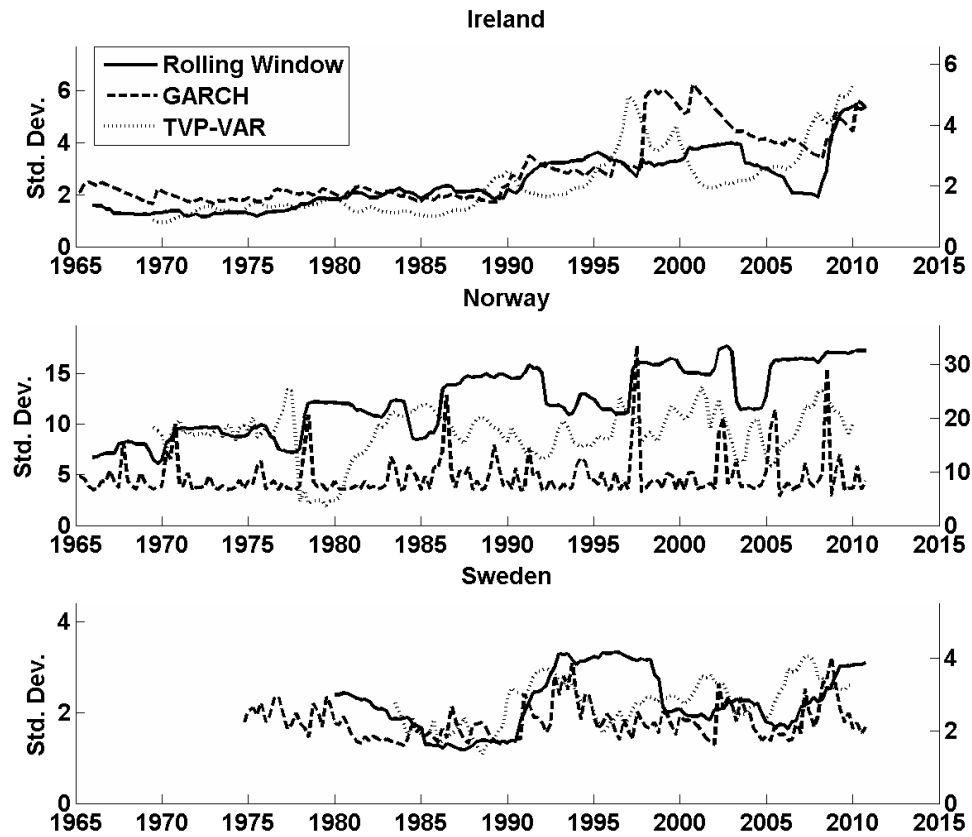


Figure 3.14: Hours Volatility: Predicted Decrease

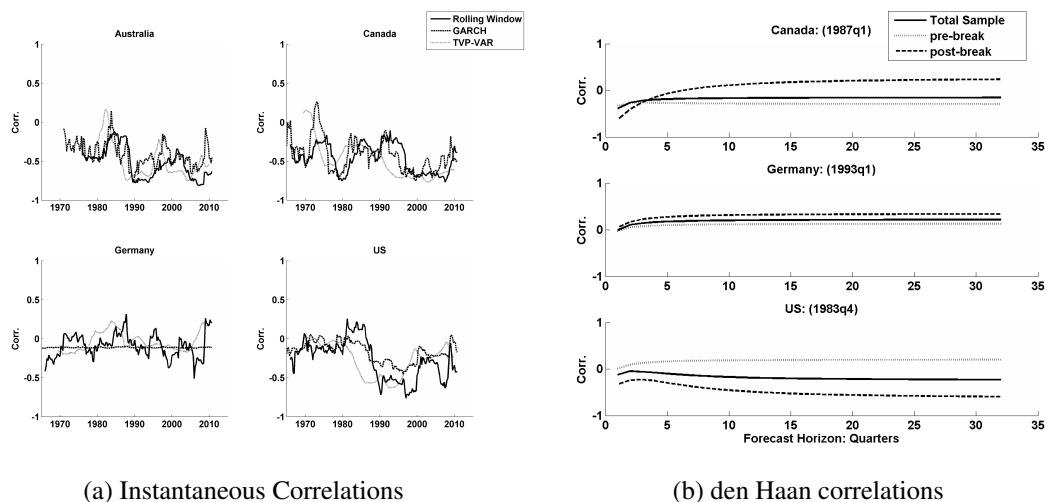


**Figure 3.15:** Volatility of Hours Relative to Output: Predicted Decrease



**Figure 3.16:** Hours Volatility: Predicted Increase



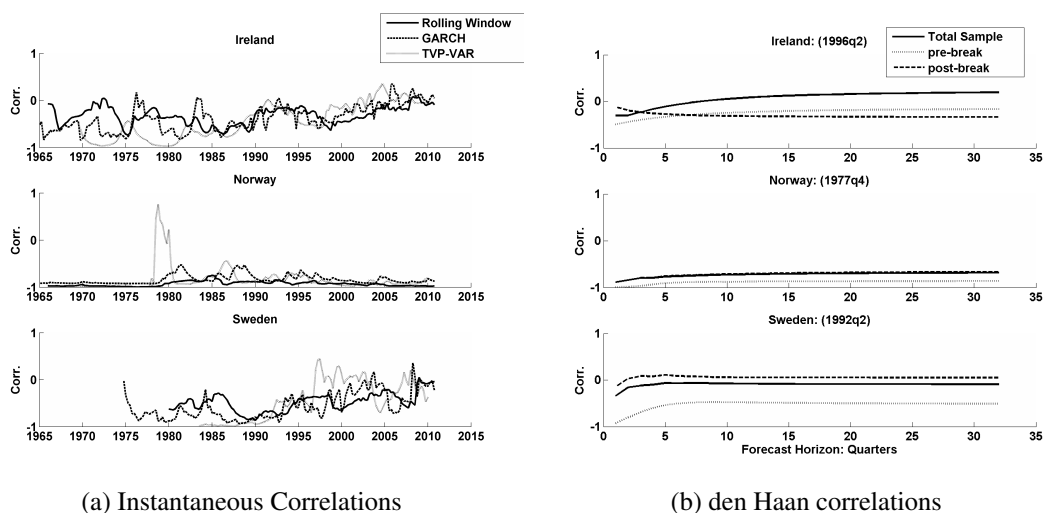


**Figure 3.17:** Correlation between productivity and hours: Predicted Decline  
 Note: The GDP break dates calculated in section 3.4.1 are in parentheses.

### 3.4.3.2 Cyclicalities of Labor Productivity

In the US, the correlation between labor productivity and both output and hours declines. We begin with the correlation between productivity and hours. Figure 3.17 plots the results for the countries that can still be consistent with the US. Figure 3.17.A plots the three instantaneous volatility measure and Figure 3.17.B plots the den Haan correlations. The US has consistent and clear results across all four methods. The instantaneous correlations in Australia and Canada decline although it is marginal. The den Haan correlations, however, are clear. Australia is the only country other than the US that exhibits a decline.

Figure 3.18 plots the productivity hours correlation for the countries that are opposite the US. Here we expect the correlation to increase. There is substantial variation in the instantaneous correlation results however the correlation marginally increases. The increase is particularly pronounced for the TVP-VAR estimation in Norway, however the other two methods also increase from essentially perfectly negative correlation. The den Haan correlations are more dramatic. Norway and Sweden clearly increase. Ireland is essentially unchanged at business cycle frequencies but exhibits a substantial increase at higher frequencies. Given the marginal instantaneous correlation results, we exclude Ireland based on the den Haan correlations.



**Figure 3.18:** Correlation between productivity and hours: Predicted Increase

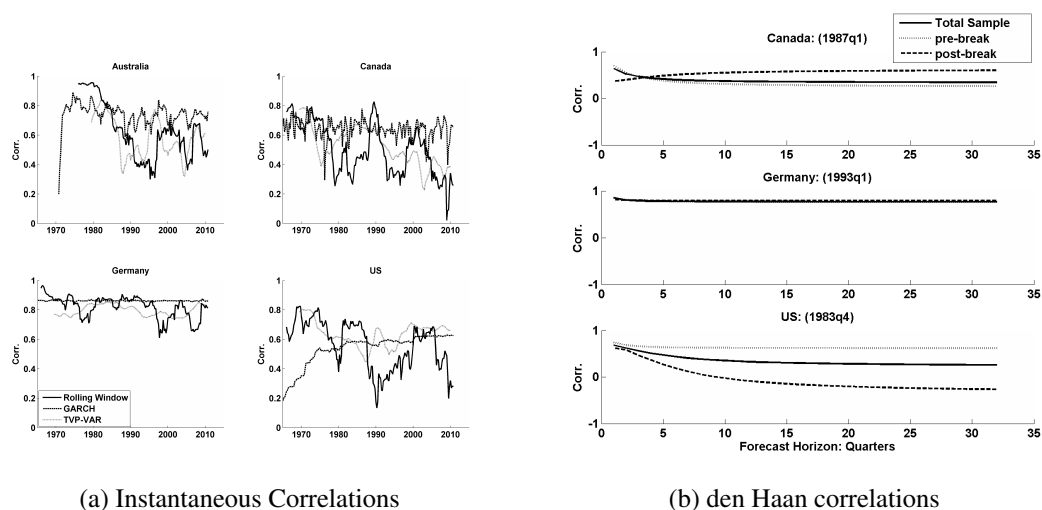
Note: The GDP break dates calculated in section 3.4.1 are in parantheses.

Figure 3.19 depicts the correlation between productivity and output for the remaining countries that can still be consistent with the US. Recall that for the US the decline in the procyclicality of labor productivity manifests itself in the split sample methods (filtering and den Haan) and the univariate conditional mean models (filtering and rolling window). Hence these results are already suspect. We see that only Canada declines under the instantaneous measures. However the den Haan correlations match what we found with hours.

Figure 3.20 depicts the results for the countries predicted to increase. Looking at the instantaneous correlations, apart from Sweden, no clear pattern emerges. For Sweden there is a rapid decline in the early 1990s that reverses over the rest of the decade and subsequently plateaus at a higher level. However in the den Haan correlations, Norway and Sweden increase substantially while Ireland declines modestly. The den Haan correlation thus match the expected signs whereas the instantaneous correlations provide much weaker evidence.

### 3.4.4 Conclusions

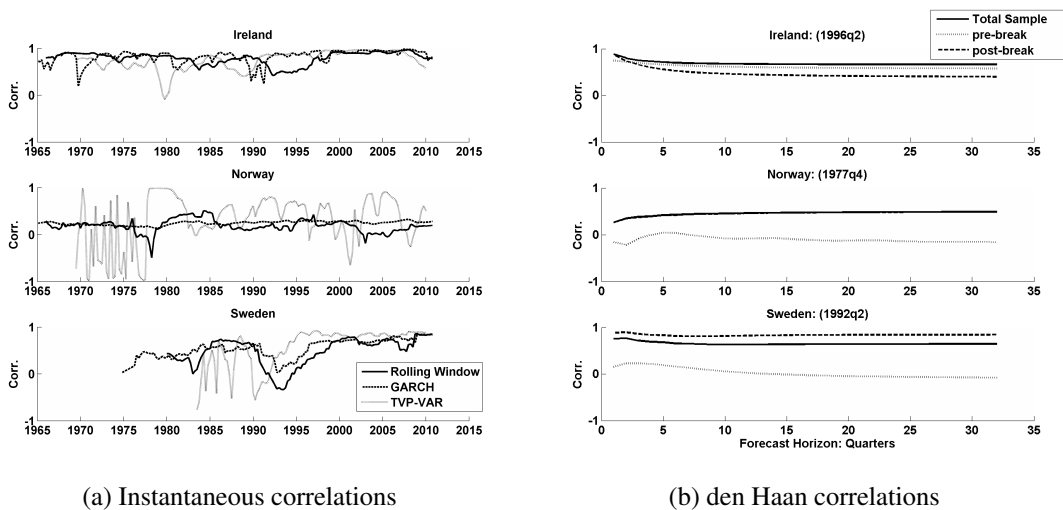
The results vary considerably across countries. In particular, only two countries have the same set of statistics as the US. However, neither country displays moments as



(a) Instantaneous Correlations

(b) den Haan correlations

**Figure 3.19:** Correlation between productivity and output: Predicted Decline  
 Note: The GDP break dates calculated in section 3.4.1 are in parantheses.



(a) Instantaneous correlations

(b) den Haan correlations

**Figure 3.20:** Correlation between productivity and output: Predicted Increase  
 Note: The GDP break dates calculated in section 3.4.1 are in parantheses.

clean as the US. The largest disagreement is the increase in the hours volatility underlying the increase in the relative volatility. This heterogeneity, in turn, suggests labor market frictions can still play a role but there is a more complicated relationship with GDP. In the next section we explore changes in labor market friction over this time period.

### 3.5 The Role of Labor Market Institutions

We explore the relationship between labor market institutions (LMI) and macroeconomic volatility and correlation dynamics in a panel setting. Our empirical setup follows Rumler and Scharler (2011). They consider how LMI's affect the volatility of the output gap and inflation using a panel of 20 OECD countries. They focus on three labor market frictions: wage bargaining centralization, union density, and employment protection legislation obtained from Nickell (2001). The output gap is represented as the difference from the HP filtered trend. Volatility of the output gap is calculated over non-overlapping 5-year periods using data over 1970-1995. This results in 6 data points for each country.

We extend this in several ways. First, we update and expand the number of LMI measures to 10. We use updated data from Nickell (2006) as well as data from the OECD and Amsterdam Institute for Advanced labour Studies (AIAS)<sup>28</sup> over the period 1970-2003. Second, we control for non-stationarity using a time-varying parameter (TVP-) VAR. Unlike the HP filter, this explicitly takes into account the multivariate structure of output and the labor market. Third, the TVP-VAR provides an annual conditional volatility measure. This expands the time series dimension from 6 to 33 points.

An alternative approach is taken by Gnocchi and Pappa (2011). They consider 13 LMI's drawn from Nickell (2006), OECD, and AIAS. Due to the lack of time variation in most of the series, they ignore the time dimension and collapse the LMI dimension using Principal Component Analysis (PCA) on the time-averages. They then consider the cross-sectional relationship between univariate filtered (HP, BK, 4D) sec-

<sup>28</sup>Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS): <http://www.uva-aias.net/208>. This expands the coverage, depth, and time period of the OECD *Employment Outlook* (1994, 1997) special chapters on collective bargaining.

ond moments (volatility and correlation) of GDP, employment, and productivity, and LMI factors. This is inapplicable given our interest in the dynamics of the second moments. Moreover, the cross-country heterogeneity in hours dynamics that we identified in section 3.4 implies time-averaging is misleading. It is not enough to know that Italy had on average higher labor market frictions and higher hours volatility than the US. It is crucial to know if changes in LMI's coincide with Italy's U-shaped pattern. If not, then the higher volatility is due to an unexplained factor in the residual correlated with the LMI's.

### 3.5.1 Labor Market Institution Data

The heterogeneity observed in section 3.4 was discussed in relation to the Galí and van Rens (2010) model. Specifically, in their model a decline in labor market frictions explains the US labor market and productivity dynamics. The labor friction are modeled as wage bargaining power and hiring and firing costs. Wage bargaining is proxied by various union measures encompassing both their extent and their power and unemployment benefits. Hiring and firing costs are proxied by employment protection legislation.

Our full specification search and details of the LMI data are documented in Appendix J. Our LMI data comes from two sources: AIAS and Nickell (2006). The labor market frictions are: i) *BRR*, OECD wage Benefit Replacement Rate (%) averaged over first 5 years of unemployment for 3 family situations and 2 money levels (Nickell); ii) *NRW*, Net Replacement Wage (%) due to Allard (2005b), incorporates tax treatment, duration, and conditions necessary to collect (Nickell) iii) *UD*, union density, percentage of workforce that is unionized (AIAS); iv) *UC*, union coverage, percentage of contracts that are negotiated by unions (Nickell).

Greater clarity on the relationship between union density and union coverage will aid in later interpretation. Union density is the proportion of all wage earners that are members of a union. Union coverage is the proportion of all wage earners *that are eligible to join a union* that are members of a union. For this reason union coverage is actually *adjusted* union coverage.<sup>29</sup> There are three ways union coverage can differ

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<sup>29</sup>See Ochel (2001).

from union density. First, employees can be prohibited from wage bargaining. All else equal, this will reduce the denominator in  $UC$  and lead to  $UC$  being greater than  $UD$ . Second, union-negotiated wage contracts can be imposed on non-union employers. All else equal, this will raise the numerator in  $UC$  and lead to  $UC$  being greater than  $UD$ . Lastly, union members may work for non-union firms. All else equal, this will raise the numerator of  $UD$  and lead to  $UC$  being smaller than  $UD$ . This last effect is only significant in Japan, therefore we expect  $UC$  to exceed  $UD$ . However, small negative differences between  $UC$  and  $UD$  do sometimes exist. This is due to different data being used to calculate the two measures and the assumptions necessary to calculate  $UC$ . For more information, see the OECD Employment Outlook (1997) and (2004). The difference between  $UC$  and  $UD$  approximates the *de facto* net effect of legislation and 3rd party agreements that extend union contracts to non-union members and restrictions on union organizing.<sup>30</sup>

Our specification is dominated by traditional wage bargaining factors. However, unions may have *de facto* influence over hiring and firing costs, even though the *de jure* government employment protection legislation is not found to be significant. A similar problem accounts for the absence of international minimum wage statistics in LMI analyses. Many European countries do not have minimum wage laws, however unions impose a *de facto*, albeit opaque, minimum wage.

### 3.5.2 Empirical Investigation

Following Rumler and Scharler (2011), we regress the volatility or correlation on our LMI's, control variables ( $X_{it}$ ), firm fixed effects ( $\mu_i$ ), and time fixed effects ( $\lambda_t$ ).

$$\begin{aligned}\sigma(y_{it}) &= \alpha_1 + \beta_1' LMI_{it} + \mu_{1i} + \lambda_{1t} + \epsilon_{1,it} \\ \sigma(n_{it}) &= \alpha_2 + \beta_2' LMI_{it} + \mu_{2i} + \lambda_{2t} + \epsilon_{2,it} \\ \rho(x_{it}, y_{it}) &= \alpha_3 + \beta_3' LMI_{it} + \mu_{3i} + \lambda_{3t} + \epsilon_{3,it} \\ \rho(x_{it}, n_{it}) &= \alpha_4 + \beta_4' LMI_{it} + \mu_{4i} + \lambda_{4t} + \epsilon_{4,it}\end{aligned}$$

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<sup>30</sup>A coarser direct measure of the *de jure* extension of union wage contracts is *ext* from AIAS that we exclude.

The results of Galí and van Rens (2010) predict that  $\beta_1, \beta_2 > 0$ , i.e. more friction results in more volatile output and hours. Similarly, we expect  $\beta_3, \beta_4 > 0$ , i.e. more friction exacerbates the labor hoarding incentive and results in more procyclical productivity.

We calculate each regression on two samples, all of the countries and restricted to the countries consistent with the Galí and van Rens (2010) identified in section 3.4. The latter are Australia, Canada, Germany, Norway, Sweden, and US. We lose Ireland due to a lack of data on union coverage. The restricted sample provides cleaner dynamics with maximum cross-country separation for our limited LMI data to fit. Whether the gain in power is overcome by the loss in sample size is an empirical question. However, these countries are not selected at random so care should be taken in interpreting the restricted results.

The results are shown in Table 3.4 with p-values in parentheses. The dependent variable is given in the column heading with both the full and restricted results. All variables are measured in percent, therefore coefficient interpretations are given as percent added rather than percent growth. Since Galí and Van Rens link reduced labor market frictions to moderation and since we did witness both growth moderation and labor market deregulation, we would expect to find the predicted relationship. Similarly, the heterogeneous labor volatility dynamics illustrated in section 3.4 would require more complicated LMI dynamics to find a relationship.

However, we find precisely the opposite. The first column shows that none of the LMI's are statistically significant in the full sample for GDP volatility. The third column shows that gross replacement rates are statistically significant in explaining hours volatility. Furthermore, the relationship with hours volatility is the correct sign and economically significant. The observed 15% average increase in benefits is associated with an increase of about 0.5% in annual hours volatility.

It is possible the Galí and van Rens (2010) (GvR) LMI mechanism is does not hold for or is not strong in all of the countries. In their calibration to US data, GvR find that their model is able to match the sign but not the magnitude of the decline in GDP volatility. Therefore, we expect the relationship between LMI's and GDP volatility to be weak. Since the model was designed to match the decline in employment volatility, that dimension provides a fairer test of the model. Unfortunately, in the full sample, reduced

labor market frictions are associated with greater employment volatility.

Restricting the sample to countries consistent with GvR, once again we arrive at counterintuitive results. Looking at the second column, we find that unadjusted unemployment benefits and union density are statistically significant and have the anticipated sign for GDP volatility. However, nothing is significant for hours volatility which GvR was designed to explain.

Turning to the correlation between labor productivity and GDP we find that union coverage, but not union density, is statistically significant and the correct sign.

In addition, net replacement rates are statistically significant for the correlation with GDP, but it has the wrong sign. When we restrict ourselves to the GvR sample, union coverage loses its significance however now both gross and net benefits are significant. In addition, they enter with opposite signs. This says that more generous unemployment benefits exacerbates the labor hoarding incentive by driving up the reservation wage, however increasing access to or lowering distortions in unemployment benefits lowers this incentive.<sup>31</sup> Although the net benefits coefficient is considered to have the wrong sign, there is an alternative general equilibrium interpretation. Easier access to unemployment benefits, holding the level constant, reduces the drag on the economy from the decrease in aggregate demand when unemployment rises. Consequently, observed equilibrium output grows more for a technology driven unit decrease in employment. Alternatively, unemployment benefits ended prior to the adjustment speed to technology driven unemployment shocks and greater duration provided more efficient aggregate demand support. In effect, the OECD gross benefit variable measured the *de jure* outcome whereas the net benefit variable comes closer to the *de facto* outcome by incorporating duration, tax distortions, and barriers to acquiring unemployment benefits.<sup>32</sup>

Finally, we find that union coverage is statistically significant and has the correct sign for the correlation between productivity and hours when using the whole sample. When we restrict the estimation to the GvR sample union coverage is no longer significant but net benefits become significant with the “wrong” sign. Again this appears to be capturing a friction in the provision of unemployment benefits.

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<sup>31</sup>The p-value on the test of the equality of the two coefficients is 0.0014.

<sup>32</sup>Estimation excluding *NRW* also finds *BRR* to be insignificant.



**Table 3.4:** Macroeconomic Dynamics and Labor Market Frictions

Panel regression of Time-Varying Parameter-VAR volatilities and correlations on labor market institutions for 12 countries from 1969-2000. *Full* denotes the 12 countries with data. Ireland is excluded due to lack of *UC* data. *Restricted* denotes the 6 countries consistent with Galí and van Rens (2010) identified in section 3.4. They are Australia, Canada, Germany, Norway, Sweden, and US.

	$\sigma(Y)$		$\sigma(L)$		$\rho(X, Y)$		$\rho(X, L)$	
	Full	Restricted	Full	Restricted	Full	Restricted	Full	Restricted
BRR	0.0203 (0.0284)	<b>0.0223</b> <b>(0.0078)</b>	<b>0.0357</b> <b>(0.0096)</b>	0.0255 (0.0116)	0.0072 (0.0076)	<b>0.0174</b> <b>(0.0034)</b>	-0.0052 (0.0063)	0.0062 (0.0062)
NRW	-0.0450 (0.0281)	0.0216 (0.0188)	0.0304 (0.0268)	0.0529 (0.0289)	<b>-0.0392</b> <b>(0.0112)</b>	<b>-0.0462</b> <b>(0.0103)</b>	-0.0122 (0.0140)	<b>-0.0535</b> <b>(0.0141)</b>
UD	-0.0343 (0.0525)	<b>0.0479</b> <b>(0.0114)</b>	0.0295 (0.0201)	0.0435 (0.0396)	0.0004 (0.0105)	0.0229 (0.0115)	-0.0032 (0.0089)	0.0198 (0.0138)
UC	0.0377 (0.0362)	0.0599 (0.0242)	-0.0478 (0.0244)	0.0005 (0.0421)	<b>0.0288</b> <b>(0.0099)</b>	0.0224 (0.0113)	<b>0.0350</b> <b>(0.0101)</b>	0.0301 (0.0141)

*NOTES:* Robust standard errors clustered over countries are reported in parantheses. Regressions include both country and time fixed-effects.

Our panel results suggest LMI's may have a greater quantitative impact on the great moderation in GDP than the GvR model suggests. However, LMI's have surprisingly little to say about the volatility in hours. One possibility is that the GvR model studied employment rather than hours. This suggests that households are able to optimize on their intensive margin to such an extent as to overcome the calibrated dynamics found in GvR. Union coverage, or the extent that employers are bound by union negotiated contracts, is associated with higher correlation between labor productivity and both GDP and hours. This *de facto* union influence is more important, in this sample, than the proportion of employees that are union members. Lastly, we uncover a negative relationship between Allard's net replacement wages and the correlation of labor productivity and both output and, to a lesser extent, hours. We suggested a possible general equilibrium interpretation that warrants further study of the barriers to receiving unemployment benefits, the adjustment speed to technology driven unemployment, and the role unemployment benefits play in setting the reservation wage.

### 3.6 Conclusion

Three possible explanations for the Great Moderation have been proposed: good luck, good policy, or structural change. Here we consider the possible role of labor

market frictions. The stylized facts in the labor market are statements of the form of non-stationarity of labor productivity correlations with output and hours and the volatility of hours. We show that these stylized facts are robust to various methods of modeling non-stationarity with the exception of the correlation between labor productivity and output. We find that this correlation remains positive except for univariate filtering and den Haan correlations. This is consistent with the existing literature using TVP-VARs however the disagreement of this moment between the models has not been stressed. In fact, theoretical models have relied solely upon filter evidence to the best of our knowledge. However, we note that the den Haan correlations have a more theoretically appealing connection to DSGE models and confirm the widely held notion that labor productivity has become less procyclical with respect to output.

Using a new internationally consistent data set on total hours, we then extend the stylized facts to thirteen additional countries. Since existing theories rely disproportionately on US data, we use the stylized facts in the US as a base case. We find significant international heterogeneity. Only two countries, Australia and Canada, have moments similar to the US. Galí and van Rens (2010) present a model that can explain all of the stylized facts using only a reduction in labor market frictions. An additional two countries, Norway and Sweden, are consistent with Galí and van Rens (2010) although they predict an increase in labor market frictions. Using data from the Amsterdam Institute for Advanced labor Studies (AIAS) on unionization and government intervention, we find that labor market frictions do not explain even these five countries. This suggests this mechanism for labor market frictions is mainly a US phenomena.

We then present the contested institutions framework of Iversen (1999). He shows there is an optimal interaction between labor markets and monetary policy that results in low output and inflation volatility. Therefore the conflicting results from the “good policy” literature and ambiguous evidence for labor market frictions may be due to a failure to jointly model monetary policy and the labor market.

With a few notable exceptions, the literature has focused almost exclusively on the US in examining the Great Moderation. The newly available hours data from Ohanian and Raffo (2011) and heterogeneity in the labor market moments argues for international comparisons of medium scale DSGEs.

Chapter 3 represents coauthored work with Thomas Daula. The dissertation author and Thomas Daula are co-first-authors.

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# Appendix A

## The Role of $\gamma$ as Unit Converter

Assume that the functional form of the household's single period felicity function is constant elasticity of substitution with housing and non-housing consumption and assume square feet is the unit by which housing is properly measured for utility purposes. This implies the following functional form:

$$\frac{\left(C^\alpha + \gamma_{f^2} H_{f^2}^\alpha\right)^{\frac{1-\rho}{\alpha}}}{1-\rho}$$

This can be rewritten as follows:

$$\frac{\left(C^\alpha + \left(\gamma_{f^2}^{\frac{1}{\alpha}} H_{f^2}\right)^\alpha\right)^{\frac{1-\rho}{\alpha}}}{1-\rho}$$

Alternatively, consider a specification where instead the proper input unit (for complementarity purposes) is square yards (a yard is three feet or 0.9144 meters). That implies the following alternative felicity function:

$$\frac{\left(C^\alpha + \gamma_{y^2} H_{y^2}^\alpha\right)^{\frac{1-\rho}{\alpha}}}{1-\rho}$$

As before, this can be rewritten so that a function of  $\gamma$  multiplies  $H_t$ :

$$\frac{\left(C^\alpha + \left(\gamma_{y^2}^{\frac{1}{\alpha}} H_{y^2}\right)^\alpha\right)^{\frac{1-\rho}{\alpha}}}{1-\rho}$$

Observe that if  $\gamma_{f^2}^{\frac{1}{\alpha}} H_{f^2} = \gamma_{y^2}^{\frac{1}{\alpha}} H_{y^2}$  then the felicity will be unchanged. This is desirable because the units of measurement alone should not determine any household decisions. By the definition of the units we know that  $9 \cdot H_{f^2} = H_{y^2}$  and similarly that  $9 \cdot P_{H_{f^2}} = P_{H_{y^2}}$ . Assuming  $\gamma_{f^2}^{\frac{1}{\alpha}} H_{f^2} = \gamma_{y^2}^{\frac{1}{\alpha}} H_{y^2}$  and making this substitution we get the following:

$$\gamma_{f^2}^{\frac{1}{\alpha}} H_{f^2} = \gamma_{y^2}^{\frac{1}{\alpha}} \cdot 9 \cdot H_{f^2} \Rightarrow \gamma_{f^2} = \gamma_{y^2} \cdot 9^\alpha$$

Is this definition of gamma sensible? One way to check is if the resulting intratemporal Euler is the correct one when everything is substituted in for the old values.

The intratemporal Euler of the square foot model is:

$$\frac{1}{\gamma_{f^2}} \cdot \left(\frac{C}{H_{f^2}}\right)^{\alpha-1} = \frac{P_c}{P_{H_{f^2}}}$$

The intratemporal Euler of the square yard model is:

$$\frac{1}{\gamma_{y^2}} \cdot \left(\frac{C}{H_{y^2}}\right)^{\alpha-1} = \frac{P_c}{P_{H_{y^2}}}$$

Substitute in  $\gamma_{y^2} \cdot 9^\alpha$  for  $\gamma_{f^2}$ ,  $\frac{H_{y^2}}{9}$  for  $H_{f^2}$  and  $\frac{P_{H_{y^2}}}{9}$  for  $P_{H_{f^2}}$ :

$$\frac{1}{\gamma_{y^2} \cdot 9^\alpha} \cdot \left(\frac{9 \cdot C}{H_{y^2}}\right)^{\alpha-1} = \frac{9 \cdot P_c}{P_{H_{y^2}}}$$

Simplify:

$$\Leftrightarrow \frac{9^{\alpha-1}}{9^{\alpha-1}} \cdot \frac{1}{\gamma_{y^2}} \cdot \left(\frac{C}{H_{y^2}}\right)^{\alpha-1} = \frac{P_c}{P_{H_{y^2}}} \Leftrightarrow \frac{1}{\gamma_{y^2}} \cdot \left(\frac{C}{H_{y^2}}\right)^{\alpha-1} = \frac{P_c}{P_{H_{y^2}}}$$

So yes, it gives the expected results. We can safely work in price per square foot and then rely on gamma to convert them into the proper utility units. However, since Flavin and Nakagawa (2008) finds that gamma is essentially 1 (1.015 page 491), this



means that the true units are extremely close to square feet. We can work backwards from gamma estimates to get the units of housing that go into the utility function:

$$\left(\frac{\gamma f^2}{\gamma^{?^2}}\right) = \left(\frac{?^2}{f^2}\right)^\alpha \Rightarrow \left(\frac{\gamma f^2}{\gamma^{?^2}}\right)^{\frac{1}{\alpha}} = \left(\frac{1.015}{1}\right)^{\frac{1}{-6.7}} = 0.9978 = \frac{?^2}{f^2}$$

The proper unit is extremely close to square feet. The model fits the utility unit of housing such that gamma is 1 at .9978 the size of a square foot. There is minimal loss of precision to measure housing services in square-feet instead.

## Appendix B

# Estimating the Effect of Adding Human Capital

There is a literature exploring the effect of human capital on portfolio choice but nothing with a serious treatment of housing . Guiso et al. (1996) considers the effects of uninsurable income risk and borrowing constraints on the household portfolio but explicitly excludes primary residence from consideration. Heaton and Lucas (2000) examines the roll of uninsurable background risks of which labor income is their canonical example. They also ignore housing in their quantitative model. Realistic integration of human capital into the setting of this paper is beyond the scope of the paper. Instead, this section treats human capital as a large but frictionlessly adjusted asset in the household portfolio alongside stocks, bonds, and housing.

Denote human capital holdings as  $M_t$  and the return on human capital as  $R_{H,t}$  . Wealth  $\tilde{W}_t$  is defined as

$$\tilde{W}_t \equiv R_f \cdot B_{t-1} + R_{m,t} \cdot X_{t-1} + P_t H_{t-1} + R_{H,t} \cdot M_{t-1}$$

where all other terms are as defined in the body of the paper. We can rewrite this as a total return on wealth equation in terms of the shares of wealth invested in each asset:

$$R_{\tilde{W}_t} \equiv \frac{\tilde{W}_t}{\tilde{W}_{t-1}} = R_f \cdot \frac{B_{t-1}}{\tilde{W}_{t-1}} + R_{m,t} \cdot \frac{X_{t-1}}{\tilde{W}_{t-1}} + P_t \frac{H_{t-1}}{\tilde{W}_{t-1}} + R_{H,t} \cdot \frac{M_{t-1}}{\tilde{W}_{t-1}}$$

In a frictionless Lucas tree economy, all asset holdings are fixed fractions of wealth determined by the expected value and covariances of their returns and household preferences. Denote these fractions respectively as  $\theta_B \equiv \frac{B_t}{\tilde{W}_t}$ ,  $\theta_X \equiv \frac{X_t}{\tilde{W}_t}$ ,  $\theta_H \equiv \frac{P_t \cdot H_t}{\tilde{W}_t}$ , and  $\theta_M \equiv \frac{M_t}{\tilde{W}_t}$ . Then the total return on wealth equation simplifies to become:

$$R_{\tilde{W}_t} = R_f \cdot \theta_B + R_{m,t} \cdot \theta_X + \frac{P_t}{P_{t-1}} \cdot \theta_H + R_{H,t} \cdot \theta_M$$

In this setting consumption  $C_t$  is also a constant fraction of wealth  $\theta_C \equiv \frac{C_t}{\tilde{W}_t} = 1 - \theta_B - \theta_X - \theta_H - \theta_M$ . This implies that the evolution of consumption is as follows:

$$C_t = \theta_C \cdot \tilde{W}_t = \theta_C \cdot R_{\tilde{W}_t} \cdot \tilde{W}_{t-1} = R_{\tilde{W}_t} \cdot C_{t-1} \Rightarrow \frac{C_t}{C_{t-1}} = R_{\tilde{W}_t}$$

Define the fraction of wealth saved:

$$\theta_s \equiv \theta_B + \theta_X + \theta_H + \theta_M$$

Define  $\theta_1$  as the fraction of wealth invested in housing and financial assets :

$$\theta_1 \equiv \theta_B + \theta_X + \theta_H = \theta_s - \theta_M$$

Define  $\theta_2$  as the fraction of wealth invested in housing and financial assets that is invested in housing:

$$\theta_2 \equiv \frac{\theta_H}{\theta_1}$$

As in the paper's body for the frictionless case,  $\theta_B$  is assumed to be zero (through a zero net supply argument). This implies:

$$R_{\tilde{W}_t} = R_{m,t} \cdot \theta_X + \frac{P_t}{P_{t-1}} \cdot \theta_H + R_{H,t} \cdot \theta_M$$

$$= \left( R_{m,t} \cdot \frac{\theta_X}{\theta_1} + \frac{P_t}{P_{t-1}} \cdot \frac{\theta_H}{\theta_1} \right) \cdot \theta_1 + R_{H,t} \cdot \theta_M$$

Also define  $\theta_2$  as the fraction of financial wealth (wealth invested but not invested in human capital) that is invested in housing:

$$\theta_2 \equiv \frac{H_t}{B_t + X_t + H_t} = \frac{\theta_H}{\theta_B + \theta_X + \theta_H}$$

$\theta_2 = \frac{\theta_H}{\theta_H + \theta_X}$  and  $1 - \theta_2 = \frac{\theta_X}{\theta_H + \theta_X}$ . Then the evolution of consumption equation can be rewritten as follows:

$$\begin{aligned} \frac{C_t}{C_{t-1}} &= R_{\bar{W}_t} = R_{m,t} \cdot \theta_X + \frac{P_t}{P_{t-1}} \cdot \theta_H + R_{H,t} \cdot \theta_M \\ &= \left[ \left( R_{m,t} \cdot \frac{\theta_X}{\theta_1} + \frac{P_t}{P_{t-1}} \cdot \frac{\theta_H}{\theta_1} \right) \cdot \theta_1 + R_{H,t} \cdot \theta_M \right] \\ &= \left( R_{m,t} \cdot (1 - \theta_2) + \frac{P_t}{P_{t-1}} \cdot \theta_2 \right) \cdot (\theta_s - \theta_M) + R_{H,t} \cdot \theta_M \end{aligned}$$

The 2004 Survey of Consumer Finance Survey establishes  $\theta_2 \approx .45$ . To estimate the consumption process predicted by this setup requires an estimate of  $\theta_M$ . Estimating individual and aggregate human capital is a complex problem that is the focus of ongoing research (see Folloni and Vittadini (2010) for a review of the history and modern attempts at measurement). Jorgenson and Fraumeni (1989) estimates the stock of America's human capital using school enrollment and demographic data. The paper finds human capital to be about 92% of the total capital stock. However, this includes the value of non-market income (especially leisure) and so the numbers are not directly comparable to  $\theta_M$  because that measure should only count resources convertible into durable and non-durable consumption. They estimate that the value of labor income only is about 18% of the total. This implies  $\theta_M = .67$ .

An alternative is to use assumptions about competition and factor shares to generate  $\theta_M$ . Kaldor (1961) documented the stable shares of income going to capital and labor. Gollin (2002b) confirms that "estimated labor shares that are essentially flat across countries and over time" and finds that two-thirds remains a good estimate for the United

**Table B.1:** Estimate of the Effect of Adding Human Capital to Model

	Std. Dev. $\Delta \ln C_t$		$\frac{M}{X+H}$ Required to Match
	$\theta_M = 0$	$\theta_M = \frac{2}{3}$	
Model (historical shocks 95-10)	No Human Capital	With Human Capital	
NIPA Non-durable Consumption	0.7%	0.7%	NA
Frictions & Housing model	3.9%	1.3%	4.6
Housing and Stock, no frictions	6.3%	2.1%	8.1
Stock Only, no frictions	10.0%	3.3%	13.3

States. In a simple model with competitive factor markets, the marginal returns of a dollar of human capital will be equalized with the marginal returns of non-human capital (machines, intellectual property, brands, and so on). Under the further assumption of constant returns to scale of production, this will equalize the returns of not just marginal capital but all capital. If all capital earns the same rate of return and human capital gets twice as large a share, then the human capital stock must be twice as large as the non-human capital stock. This implies that  $\theta_M$  is roughly two-thirds and  $\theta_s - \theta_M$  is roughly one-third and matches almost perfectly estimates of Jorgenson and Fraumeni (1989).

Lacking updated time series data on the return to human capital, it is approximated with a constant growth of 2% per year. Under the assumptions, the effects on consumption variance in the frictionless models are exact. In the housing and frictions model, the human capital cannot be added simply as another asset as it can in the frictionless models. Instead, the paper assumes that  $\theta \cdot W_t$  is invested in human capital but the same consumption policy holds as without human capital. Table B.1 shows the results of this simplified treatment of human capital alongside the paper's preferred calibration without them. Introducing a large and risk-less asset to the household balance sheet delivers the intuitive result that wealth is less volatile and therefore so is consumption.

## **Appendix C**

# **Categorizing SEC filings by Anticipator and Importance**

This paper makes use of correspondence with a corporate lawyer, an executive compensation consultant, and two mergers and acquisitions investment bankers to better understand which filings were important if they were scheduled or unanticipated. If you asked enough market participants and regulators you could probably find someone for each filing willing to say that it is important. However, this list reflects the consensus of the correspondents, and especially with the major releases few would quibble with the resulting categorization.

**Table C.1: Major Importance SEC Filings in Study**

Full Name	File As	Define	Generally an Anticipated Filing?
3/A	3, 3/A	Initial statement of beneficial ownership of securities	No
5	5, 5/A	Annual statement of changes in beneficial ownership of securities	Yes
8-A12B/A	8-A12B, 8-A12B/A	Form for the registration / listing of a class of securities on a national securities exchange pursuant to section 12(b)	No
8-A12G	8-A12G, 8A12G/A	Form for registration of a class of securities pursuant to section 12(g)	No
8-K/A	8-K, 8-K/A	Amended Current report filing	No
8-K	8-K, 8-K/A	Current report filing. Interim report which announces any material events or corporate changes that occur between 10-Q quarterly reports.	No
ARS	ARS, ARS/A	Annual report to security holders	Yes
DEF 14A	DEF 14A	Definitive proxy statements	Yes
DEFA14A	DEF 14A	Definitive additional proxy soliciting materials including Rule 14(a)(12) material. Submission type DEFA14A can be filed as part of Form 8-K.	Yes
13F-HR/A	Form 13 F	Amendment of Initial Quarterly Form 13F Holdings report filed by institutional managers	No
425	Form 425	Filing under Securities Act Rule 425 of certain prospectuses and communications in connection with business combination transactions	No
RW	Form RW	Registration Withdrawal Request	No
5/A	N-5, N-5/A	Registration statement for small business investment companies	No
NT 10-K	NT 10-K, NT 10-K/A	Notice under Rule 12b25 of inability to timely file all or part of a form 10K, 10-KSB, or 10-KT or Amendment	No
NT 10-Q	NT 10-Q, NT 10Q/A	Notice under Rule 12b25 of inability to timely file all or part of a form 10-Q or 10-QSB	No
POSASR	S-3	Post-effective Amendment to an automatic shelf registration statement on Form S-3ASR or Form F-3ASR	No

**Table C.2: Moderate Importance SEC Filings in Study**

Full Name	File As	Define	Generally an Anticipated Filing?
11-K	11-K, 11-K/A	Annual report of employee stock purchase, savings and similar plans	Yes
144/A	144, 144/A	Filing for proposed sale of securities under Rule 144	No
15-12B	15-12B, 15-12B/A	Notice of termination of registration of a class of securities under Section 12(b)	No
PX14A6G	DEFINITIVE MATERIALS (PROXY MATERIALS)	Notice of exempt solicitation	No
13F-HR	Form 13 F	Initial Quarterly Form 13F Holdings report filed by institutional managers	Yes
NT 10-K/A	NT 10-K, NT 10-K/A	Notice under Rule 12b25 of inability to timely file all or part of a form 10K, 10-KSB, or 10-KT or Amendment	No
PRER14A	REVISED PRELIMINARY MATERIALS	Preliminary revised proxy soliciting materials	No
S-1	S-1	General form of registration statement for all companies including face-amount certificate companies	No
POS AM	S-1	Post-effective amendment to a registration statement that is not immediately effective upon filing	No
S-3DPOS	S-3	Post-effective amendment to a S-3D registration statement	No
S-3ASR	S-3	Automatic shelf registration statement of securities of well-known seasoned issuers	Yes
S-3D	S-3	Automatically effective registration statement for securities issued pursuant to dividend or interest reinvestment plans	Yes
S-3	S-3	Registration statement for specified transactions by certain issuers	Yes
S-3/A	S-3	Pre-effective amendment	Yes
S-4	S-4, S-4/A	Registration of securities issued in business combination transactions	No
S-4/A	S-4, S-4/A	Pre-effective amendment	No
SC 13D	Schedule 13D	Schedule filed to report acquisition of beneficial ownership of 5% or more of a class of equity securities	No
SC 13D/A	Schedule 13D	Schedule filed to report acquisition of beneficial ownership of 5% or more of a class of equity securities	No
SC 13G	Schedule 13G	Schedule filed to report acquisition of beneficial ownership of 5% or more of a class of equity securities by passive investors and certain institutions	No
SC 13G/A	Schedule 13G	Schedule filed to report acquisition of beneficial ownership of 5% or more of a class of equity securities by passive investors and certain institutions	No



**Table C.3: Minor Importance Unanticipated SEC Filings in Study**

Full Name	File As	Define	Generally an Anticipated Filing?
3	3, 3/A	Initial statement of beneficial ownership of securities	No
4	Form 4	Statement of changes in beneficial ownership of securities	No
25	25, 25/A	Notification filed by issuer to voluntarily withdraw a class of securities from listing and registration on a national securities exchange	No
144	Form 144	Filing for proposed sale of securities under Rule 144	No
10-12B/A	10-12B, 10-12B/A	Initial general form for registration of a class of securities pursuant to section 12(b)	No
10-Q/A	10-Q	Amendment of Quarterly report pursuant to sections 13 or 15(d)	No
25-NSE	25-NSE, 25NSE/A	Notification filed by national security exchange to report the removal from listing and registration of matured, redeemed or retired securities	No
4/A	Form 4	Statement of changes in beneficial ownership of securities	No
424B2	424 PROSPECTUS	Prospectus filed pursuant to Rule 424(b)(2)	No
424B3	424 PROSPECTUS	Prospectus filed pursuant to Rule 424(b)(3)	No
424B5	424 PROSPECTUS	Prospectus filed pursuant to Rule 424(b)(5)	No
424B8	424 PROSPECTUS	Prospectus filed pursuant to Rule 424(b)(8)	No
8-A12B	8-A12B, 8-A12B/A	Form for the registration / listing of a class of securities on a national securities exchange pursuant to section 12(b)	No
DEL AM	Rule 473 Delaying Amendment	Separately filed delaying amendment under Securities Act Rule 473 to delay effectiveness of a 1933 Act registration statement	No
NT 11-K	NT 11-K, NT 11K/A	Notice under Rule 12b25 of inability to timely file all or part of a form 11-K	No
PRE 14A	PRELIMINARY MATERIALS (PROXY MATERIALS)	Preliminary proxy statement not related to a contested matter or merger / acquisition	No
PREC14A	PRELIMINARY MATERIALS (PROXY MATERIALS)	Preliminary proxy statement in connection with contested solicitations	No
S-8	S-8	Initial registration statement for securities to be offered to employees pursuant to employee benefit plans	No
S-8 POS	S-8 POS	Post-effective amendment to a S-8 registration statement	No
SC TO-C	Schedule TO-C	Written communication relating to an issuer or third party tender offer	No
SC TO-T	Schedule TO-T	Third party tender offer statement	No
SC TO-T/A	Schedule TO-T	Third party tender offer statement	No

**Table C.4: Minor Importance Anticipated SEC Filings in Study**

Full Name	File As	Define	Generally an Anticipated Filing?
10-K	10-K	Annual report pursuant to section 13 and 15(d)	Yes
10-K/A	10-K	Annual report pursuant to section 13 and 15(d)	Yes
10-Q	10-Q	Quarterly report pursuant to sections 13 or 15(d)	Yes
DEFC14A	DEF 14A	Definitive proxy statement in connection with contested solicitations	Yes
DEFN14A	DEF 14A	Definitive proxy statement filed by non management	Yes
DEFR14A	DEF 14A	Definitive revised proxy soliciting materials	Yes
DFAN14A	DEF 14A	Definitive additional proxy soliciting materials filed by non-management including Rule 14(a)(12) material. Can be filed as part of 8-k.	Yes

## Appendix D

# Average Waiting Time Declines with the Inverse of the Number of Trades

The NYSE is open from 9:30 to 4:00, or 6.5 hours of trading. Assume that trades can only occur during these hours. Suppose there are  $N$  trades that they are completed instantly. Let  $X_i$  be the time that trade  $i$  occurs. Let it be distributed with an arbitrary distribution  $F$  with domain  $[9.5, 16]$ . Define a new sequence  $Y_i$  by sorting the trades from the earliest  $Y_1 = \min(X_i, i = 1 \dots N)$  to latest  $Y_N = \max(X_i, i = 1 \dots N)$ . Define  $Z_j$  as the waiting time between the  $j^{th} + 1$  trade and the  $j^{th}$  trade, that is  $Z_0 = Y_1, Z_1 = Y_2 - Y_1$  and so on, until  $Z_N = 16 - Y_N$ . The average time between trades is:

$$\bar{Z} = \frac{1}{N} \cdot \sum_{j=0}^N Z_j$$

Consider the simple example of a day with 1 trade. Half the day is spent waiting for the the first trade and half the time is spent waiting afterwords, so the total time waiting is one day. This makes it clear that adding up the time spent waiting always equals one and  $\sum_{j=0}^N Z_j$ . Plugging into our average waiting time formula,  $\bar{Z} = \frac{1}{N}$ . If the trades are not instantaneous, taking time  $t_{trade}$  each, then  $\sum_{j=0}^N Z_j$  is not one as before but  $\max(1 - t_{trade} \cdot N, 0)$ . In this case  $\bar{Z} = \frac{1}{N} \cdot \max(1 - t_{trade} \cdot N, 0)$ . As long as the entire day is not spent trading (in which case waiting times are zero), this gives an average waiting time of  $\bar{Z} = \frac{1}{N} - t_{trade}$  and waiting times still decline with the inverse

of the number of trades.

The reader may object that the final period is not a real waiting time. The trader must continue waiting until the next trading day when they can again trade. To model a multi-day setting, enrich the notation so that a super script indicates the date such that  $Z_j^k$  indicates the waiting time of the  $j^{th}$  trade on the  $k^{th}$  day. Let the number of trades on the  $k^{th}$  day be  $N_k$ . Then  $Z_j^1$  for is identical to the old  $Z_j$ , except for the final value  $Z_{N_1}^1$ , which no longer exists, Instead traders know that after the last trade of the day (at  $Y_N^1$ ) we have to wait until the first trade of the next day ( $Y_1^2$ ). Therefore, for  $k > 1$ ,  $Z_1^k = (16 - Y_n^{k-1}) + 17.5 + Y_1^k$ , that is, traders have to wait until the end of trading day, the 17.5 hours the market is closed, and then until the next trade.

Now calculate the average waiting time between trades across multiple days (K). After the last trade on the last day, there is no more trading, and so no more waiting between trades  $Z_{N_K}^K = 0$

$$\bar{Z} = \frac{1}{\sum_{i=1}^K N_k} \sum_{k=1}^K \left[ \sum_{j=0}^{N_k-1} Z_j^k \right]$$

Again, summing all the waiting times from  $Z_0^1$  to  $Z_{N_K}^K$  is the length of time between the start of trading of the first trading day to the time of the last trade on the last day. This is less than the number of days in the sample (K).

$$\sum_{k=1}^K \left[ \sum_{j=0}^{N_k-1} Z_j^k \right] \leq K \cdot 24$$

Which implies that the waiting period satisfies the following inequality:

$$\bar{Z} \leq \frac{K \cdot 24}{\sum_{i=1}^K N_k}$$

So the average waiting time is still declines with one over the number of trades. If trades take finite time then the total waiting time is not  $K \cdot 24$  but  $K \cdot 24 - \sum_{i=1}^K N_k \cdot t_{trade}$ . Substituting this into the equation above gives

$$\bar{Z} \leq \frac{K \cdot 24 - \sum_{i=1}^K N_k \cdot t_{trade}}{\sum_{i=1}^K N_k} = \frac{K \cdot 24}{\sum_{i=1}^K N_k} - t_{trade}$$

which also declines with the inverse of the total number of trades.

The above analysis abstracts from the heterogeneous number of shares traded in each trade. In reality, though most trades are in round lots, there is considerable variation in the number of shares traded in each trade. A trader or market maker might instead ask “how long must I wait to trade a fixed number of shares” rather than “how long must I wait to trade any shares?” In this case the results are similar. First, assume that all trades are of a fixed size  $s_{trade}$ . Then assuming all trading opportunities are two-way markets, the expected waiting time to reverse a position of size  $s_{position}$  is the expected time for  $\frac{s_{position}}{s_{trade}}$  trades to occur. By the linearity of the expectation operator over random variables with finite expectations, this is proportional to  $\frac{s_{position}}{s_{trade}} \cdot \frac{1}{N}$  so this too declines with  $\frac{1}{N}$ .

This also extends to the case of variable trade size. When all trades are not of equal size assume a minimum lot size  $s_{min}$ . Now larger trades are multiples of the minimum lot size, and this framework models them as  $M_i = s_{trade,i}/s_{min}$  trades. There is a new total number of trades  $\tilde{N} = \sum_{i=1}^N M_i$  and average wait times decline with  $\frac{1}{\tilde{N}}$ . From the perspective of a trader waiting to fill an order of a fixed size  $s_{position} > s_{min}$ , an increase in the lot size of 10% or an increase in the the number of trades of 10% are equivalent.

## Appendix E

# Effect of S.E.C. Filings Change Percent Spreads

This repeats table 4 from the paper but instead of only including dates with filings, it includes all the dates for the 10 large and ten small firms in the study.

**Table E.1:** Do S.E.C. Filings Change Percent Spreads?

VARIABLES	(1) IVD Larger Firms (1)	(2) IVD Smaller Firms (0)	(3) Log Vol. Larger Firms (1)	(4) Log Vol. Smaller Firms (0)
IVD	1.625e+05*** (4.555e+04)	2.887e+00 (3.762e+00)		
$\Delta$ Log Vol.			-4.518e-04** (1.434e-04)	-2.831e-04 (2.539e-04)
Unanticipated Filing	-3.904e-07 (1.892e-05)	1.923e-04 (2.068e-04)	-1.829e-06 (1.911e-05)	2.017e-04 (2.065e-04)
Anticipated Filing	-7.116e-06 (3.327e-05)	-2.548e-04 (5.036e-04)	-8.582e-06 (3.226e-05)	-2.440e-04 (5.012e-04)
Constant	-1.101e-06 (1.287e-05)	-2.396e-05 (7.590e-05)	-5.510e-07 (1.311e-05)	-2.461e-05 (7.587e-05)
Observations	2730	2661	2730	2661
$R^2$	0.040	0.001	0.016	0.001
Adj. $R^2$	0.0392	-0.000478	0.0145	-1.88e-05

Robust standard errors in parentheses

\*\*\* p<0.001, \*\* p<0.01, \* p<0.05

## **Appendix F**

# **Effect of Alternate Earnings Estimate Surprise Measures**

Earnings in Estimate Range means that the earnings estimate was between the highest and lowest IBES estimates. Earnings % Surprise is the fraction by which a firm missed its estimate and can be positive or negative.  $\text{Min}(\% \text{ Surprise}, 0)$  is the same as the last measure but truncated so only negative surprises are counted. Positive surprises are zero. Earnings Made Estimate is a still simpler measure, an indicator variable if earnings were greater or equal to the estimate.

**Table F.1:** Alternate Estimate Surprise Measures Give the Same Result

VARIABLES	(1) Log Vol. Made Est.	(2) Log Vol. Earnings in Est. Range	(3) Log Vol. Percent Surprise	(4) Log Vol. Neg. Surprise Size
$\Delta$ Log \$ Volume	-1.885e-03*** (1.651e-04)	-1.885e-03*** (1.652e-04)	-1.886e-03*** (1.651e-04)	-1.886e-03*** (1.651e-04)
Std. of Earnings Est.	3.157e-06 (8.860e-06)	3.476e-06 (8.809e-06)	3.367e-06 (8.824e-06)	3.451e-06 (8.810e-06)
Earnings in Est. Range		2.990e-05 (1.082e-04)		
Earnings % Surprise			-4.858e-06 (5.799e-06)	
Min(%Surprise,0)				-1.240e-06 (7.016e-06)
Earnings Made Est.	-1.069e-04			
Constant	2.407e-04** (8.274e-05)	1.937e-04** (7.344e-05)	1.992e-04** (6.131e-05)	1.999e-04** (6.126e-05)
Observations	16823	16823	16823	16823
$R^2$	0.016	0.016	0.016	0.016
Adj. $R^2$	0.0157	0.0157	0.0157	0.0157

Robust standard errors in parentheses

\*\*\* p&lt;0.001, \*\* p&lt;0.01, \* p&lt;0.05

## Appendix G

# Converting GDP and Hours Estimates to Productivity Estimates

Let  $y_t$  be output and  $\ell_t$  be hours, both in logs. Then log productivity is given by  $x_t = y_t - \ell_t$ . Given variances and covariances of output and hours, we can determine variances and covariances with productivity by simple identities.

The variance of productivity is given by

$$\begin{aligned} \text{Var}(x_t) &= \text{Var}(y_t - \ell_t) \\ &= \text{Var}(y_t) + \text{Var}(\ell_t) - 2\text{Cov}(y_t, \ell_t) \end{aligned}$$

The covariance between productivity and output is derived as follows

$$\begin{aligned} \text{Cov}(x_t, y_t) &= \text{Cov}(y_t - \ell_t, y_t) \\ &= \text{Cov}(y_t, y_t) - \text{Cov}(y_t, \ell_t) \\ &= \text{Var}(y_t) - \text{Cov}(y_t, \ell_t) \end{aligned}$$

The covariance between productivity and hours is derived as follows



$$\begin{aligned} \text{Cov}(x_t, \ell_t) &= \text{Cov}(y_t - \ell_t, \ell_t) \\ &= \text{Cov}(y_t, \ell_t) - \text{Cov}(\ell_t, \ell_t) \\ &= \text{Cov}(y_t, \ell_t) - \text{Var}(\ell_t) \end{aligned}$$

# Appendix H

## Time-varying parameter VAR

### H.1 Priors

The prior assumption that the VAR is stationary is imposed by multiplying the conditional density of the coefficients by an indicator function that is one if the roots of the VAR polynomial are all outside the unit circle. To be precise, let  $z^T$  denote a sequence of  $z$ 's up to time  $T$ . The conditional prior density is given by

$$p(\theta^T | \alpha^T, \sigma^T, V) \propto I(\theta^T) f(\theta^T | \alpha^T, \sigma^T, V)$$

where  $I(\theta^T) = \prod_{t=0}^T I(\theta_t)$  is the product of indicators for each time time  $t$ . The conditional distribution further be decomposed by using the Markov property of the random walk on the coefficients.

$$f(\theta^T | \alpha^T, \sigma^T, V) = f(\theta_0) \prod_{t=1}^T f(\theta_t | \theta_{t-1}, \alpha^T, \sigma^T, V) \quad (\text{H.1})$$

The prior densities are calibrated by estimating a time-invariant VAR using the first ten years of data for each country. The prior densities and calibrations follow from Benati and Mumtaz (2007) and Primiceri (2005).

$$\begin{aligned}
p(\theta_0) &\propto I(\theta_0)N(\hat{\theta}_{OLS}, \hat{V}(\hat{\theta}_{OLS})) \\
p(2 \log \sigma_0) &= N(2 \log \hat{\sigma}_{OLS}, 10 \times I) \\
p(\alpha_0) &= N(\hat{\alpha}_{OLS}, |\hat{\alpha}_{OLS}|) \\
p(Q) &= IW(\bar{Q}^{-1}, T_0) \\
p(S_i) &= IW(\bar{S}^{-1}, i + 1) \\
p(W_{i,i}) &= IG\left(\frac{1}{2}, \frac{k_W}{2}\right)
\end{aligned}$$

where  $\hat{\theta}_{OLS}$  is the vector of OLS estimates of the VAR coefficients and  $\hat{V}(\hat{\theta}_{OLS})$  is the associated covariance matrix using the initial sample of size  $T_0$ .  $\hat{\alpha}_{OLS}$  and  $\hat{\sigma}_{OLS}$  are the corresponding vectors from the decomposition of the OLS residual covariance matrix,  $\hat{A}\hat{\Omega}_{OLS}\hat{A}' = \hat{\Sigma}\hat{\Sigma}'$ .  $\bar{Q} = k_Q \times V(\hat{\theta}_{OLS})$  and  $\bar{S} = k_S \times |\hat{\alpha}_{OLS}|$ .  $(k_Q, k_S, k_W) = (0.005, 0.00001, 0.0001)$  denote tuning parameters on the prior variances. Primiceri (2005) p.841-843 discusses how these tuning parameters determine the prior probability of time variation and provides details on a reversible jump MCMC method for choosing them.

## H.2 Estimation

The Gibbs sampler proceeds by iteratively drawing from the conditional distribution of the current parameter, conditioning on past values and any realizations from the current iteration. Under regularity conditions, the iterations will eventually draw realizations from the true joint distribution. The following discussion maintains the assumption from the paper that the state equations follow a random walk. More general forms of the estimation can be found in Primiceri (2005).

**Step 1:**  $p(\theta^T | z^T, \alpha^T, \sigma^T, V)$

The conditional distribution is Normal. Draws from the posterior are obtained via the Carter and Kohn (1994) algorithm. First, the coefficients,  $\theta_{t|t}$ , and precision matrices,  $P_{t|t}$ , are estimated by the Kalman Filter. The state-space is given by

$$z_t = G_t' \theta_t + A_t^{-1} \Sigma_t \epsilon_t$$

$$\theta_t = \theta_{t-1} + \nu_t$$

and the familiar Kalman Filter recursion equations are employed. The final period coefficient is then drawn from the Normal distribution centered at the Kalman Filter estimates,  $\hat{\theta}_T \sim N(\theta_{T|T}, P_{T,T})$ . The mean and variance of the remaining coefficients follows the backward recursion

$$\theta_{t|t+1} = \theta_{t|t} + P_{t|t} P_{t|t+1}^{-1} (\hat{\theta}_{t+1} - \theta_{t|t})$$

$$P_{t|t+1} = P_{t|t} P_{t+1|t}^{-1} P_{t|t}$$

Where the coefficients are drawn according to  $\hat{\theta}_t \sim N(\theta_{t|t+1}, P_{t|t+1})$ .

**Step 2:**  $p(\alpha^T | z^T, \theta^T, \sigma^T, V)$

This is done following the same procedure as in Primiceri (2005). This involves transforming the the measurement equation such that the Carter-Kohn algorithm can be employed. Specifically, we can rewrite the the state-space as

$$A_t \hat{z}_t = \Sigma_t \epsilon_t$$

$$\alpha_t = \alpha_{t-1} + \zeta_t$$

where  $\hat{z}_t = G_t' \theta_t$  is known given  $\theta^T$ . The lower-triangular structure of  $A_t$  and diagonal  $\Sigma_t$  allows the Carter-Kohn algorithm to be employed equation by equation.

**Step 3:**  $p(\sigma^T | z^T, \theta^T, \alpha^T, V)$

Application of the Carter-Kohn algorithm is no longer simple. The state-space is now

$$\begin{aligned}\hat{z}^* &= \Sigma_t \epsilon_t \\ \log \sigma_t &= \log \sigma_{t-1} + \eta_t\end{aligned}$$

which is non-linear in  $\Sigma_t$ . We employ the univariate algorithm by Jacquier, Polson, and Rossi (2004) for each element  $\sigma_{i,t}$ . Details for this application can be found in Cogley and Sargent (2005).

Note that Primiceri (2005) uses a different algorithm. He log-linearizes the measurement equation and invokes the Carter-Kohn algorithm. However the error term is no longer Normal. Therefore there is an additional step that uses Kim et al. (1998)'s mixture of Normals approximation to  $\log \epsilon_t$ . For those interested in this approach, a more accurate approximation to  $\log \epsilon_t$  can be found in Omori et al. (2007).

**Step 4:**  $p(V|z^T, \theta^T, \alpha^T, \sigma^T)$

Under the assumption that the block-diagonal elements of  $V$  are independent and the conjugate prior specification of our covariance matrices, we can draw separately from each conditional distribution using standard techniques. These are standard draws from Normal-Inverse Wishart and Normal-Inverse Gamma setups.

# Appendix I

## Labor Friction Model

There are two labor frictions in the model; endogenous effort choice and convex labor adjustment costs. Endogenous effort choice provides an intensive margin that is not subject to the adjustment cost. The two shocks in the economy are technology shocks and consumption preference shocks. Both shocks follow AR(1) processes.

First start with a completely flexible labor market. Assuming effort has stronger diminishing returns in production and higher marginal disutility than employment, then the intensive margin is never used to adjust. Thus in a completely flexible market only employment adjusts. This leads to the following equilibrium equations

$$\begin{aligned}n_t &= (1 - \eta)a_t + z_t \\y_t &= a_t + (1 - \alpha)z_t\end{aligned}$$

where  $n_t$  is employment,  $y_t$  is output,  $a_t$  is the technology shock, and  $z_t$  is the preference shock, all in logs. The parameters  $\eta \in [0, 1]$  and  $\alpha \in (0, 1)$  are the inverse of the intertemporal elasticity of substitution and diminishing returns to total labor, respectively. This leads to the following covariances

$$\begin{aligned}\text{cov}(y_t - n_t, y_t) &= \eta \text{var}(a_t) - \alpha(1 - \alpha) \text{var}(z_t) \\ \text{cov}(y_t - n_t, n_t) &= \eta(1 - \eta) \text{var}(a_t) - \alpha \text{var}(z_t)\end{aligned}$$

We are interested in how these change in response to a change in labor market frictions. However, for logarithmic utility over consumption ( $\eta = 1$ ) we can unambiguously sign labor productivity as being countercyclical with respect to employment. The last moment we are interested in is the volatility of labor input relative to the volatility of output

$$\frac{\text{var}(n_t)}{\text{var}(y_t)} = \frac{(1 - \eta)^2 \text{var}(a_t) + \text{var}(z_t)}{\text{var}(a_t) + (1 - \alpha)^2 \text{var}(z_t)}$$

For the case of infinite labor market frictions, no new workers will be hired. Therefore, all labor adjustment will occur along the intensive margin. This leads to the following equilibrium equations

$$\begin{aligned} e_t &= (1 - \eta)a_t + z_t \\ y_t &= (1 + \phi)a_t + (1 - \alpha)\psi z_t \end{aligned}$$

where the parameters  $\phi \geq 0$  and  $\psi \in [0, 1]$  represent the marginal disutility of effort and the diminishing return to effort in production, respectively. Output then responds more aggressively to technology shocks but less to preference shocks. This leads to the following covariances

$$\begin{aligned} \text{cov}(y_t - e_t, y_t) &= (1 + \phi)(\phi + \eta)\text{var}(a_t) + (1 - \alpha)[(1 - \alpha)\psi - 1]\text{var}(z_t) \\ \text{cov}(y_t - e_t, e_t) &= (\phi + \eta)(1 - \eta)\text{var}(a_t) + [(1 - \alpha)\psi - 1]\text{var}(z_t) \end{aligned}$$

Notice that the response to preference shocks are equivalent if  $\psi = 1$ . Thus  $\psi$  leads to a more negative response to preference shocks. However this is offset by the increased response to technology shocks.

Galí and van Rens (2010) show in their calibration that the larger technology shocks relative to preference shocks drive the US results.

# Appendix J

## Labor Market Institutions Data

The labor market institution (LMI) data are drawn from the OECD<sup>1</sup>, Nickell (2006)<sup>2</sup>, and AIAS<sup>3</sup>. Table J.1 lists the variables investigated in our specification search. It also includes the source, source's variable name, and maximum dates available. This lists all variables used in both Gnocchi and Pappa (2011) and Rumler and Scharler (2011). Our final variable selection can be found in section 3.5.

**Table J.1: Labor Market Institution Data Sources**

Name	Variable	Source	Dates	Notes
Employment Protection Legislation (EPL)	epl_allard	Nickell	1960-2003	Details in Allard (2005a)
EPL: Regular Employment	epl_r	OECD	1985-2008	Version 1
EPL: Temporary Employment	epl_t	OECD	1985-2008	Version 1
EPL: Collective Dismissals	epl_cd	OECD	1998-2008	
Wage Coordination	wcoord	AIAS	1960-2010	
Wage Coordination	cowint	Nickell	1960-2000	Used in Rumler and Scharler (2011)
Union Density	ud	AIAS	1960-2010	
Union Density	udnet_vis	Nickell	1960-2004	Used in Rumler and Scharler (2011)
Union Coordination	uc	Nickell	1960-2000	
Unemployment: Wage Replacement Rate	brr_oecd	Nickell	1960-2003	
Unemployment: Wage Replacement Rate	nrw	Nickell	1960-2003	Details in Allard (2005b) <sup>1</sup>
Level of wage bargaining	level	AIAS	1960-2010	
Government intervention in wage setting	govtint	AIAS	1960-2010	
Union concentration	conc	AIAS	1960-2010	
Union centralization	cent	AIAS	1960-2010	
Mandatory extension of union contracts to non-unions	ext	AIAS	1960-2010	
Minimal Wage Setting	mws	AIAS	1960-2010	

Notes:

1) Includes the effective taxes and transfers in unemployment benefits' measure.

<sup>1</sup>Labour/Employment Protection at <http://stats.oecd.org>

<sup>2</sup>The dataset and definitions can be found at: <http://eprints.lse.ac.uk/19789/>

<sup>3</sup>Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS): <http://www.uva-aias.net/208>. Data definitions can be found at: [http://www.uva-aias.net/uploaded\\_files/regular/ICTWSScodebook30\(2\).pdf](http://www.uva-aias.net/uploaded_files/regular/ICTWSScodebook30(2).pdf).