Since the Great Recession a large body of business cycle research has focused on the role of investment. A defining characteristic of investment projects is time to build, which this paper documents to exhibit substantial countercyclical variation. I develop a general equilibrium model where time to build is a consequence of search frictions in capital supply. Longer time to build injects uncertainty into the investing firm’s planning problem, and lowers investment and GDP through capital misallocation. The calibration strategy jointly targets the investment rate distribution and time series fluctuations in time to build. For the last two severe recessions, the calibrated model explains a third of the contraction in GDP and investment. I corroborate the results in a structural VAR model.

Keywords: Time to Build, Business Cycles, Investment, Misallocation.

1. INTRODUCTION

Despite the long tradition of business cycle research in macroeconomics, much remains to be learned. In fact, the Great Recession had a tremendous effect on business cycle research shifting the focus toward investment, including the rapidly growing literatures on uncertainty shocks and financial frictions.1 One important feature of investment projects is the waiting time between order and delivery, which is the definition of time to build used in this paper.2 Empirically, time to build fluctuates between three and nine months with peak values during recessions. While modern, dynamic macroeconomic models do assume constant time to build, this masks the substantial countercyclical variation in the data.

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1I am extremely thankful to my advisors, Christian Bayer and Keith Kuester, for their guidance and support. I also thank Benjamin Born, Greg Kaplan, Ben Moll, Jürgen von Hagen, and numerous seminar participants in Bonn and the CEF 2016 for useful comments at various stages of the project.

2To name but a few, Bloom (2009) and Bachmann and Bayer (2013) study the impact of uncertainty shocks, Christiano et al. (2014) highlights the interaction of uncertainty shocks with financial frictions, Khan and Thomas (2013) studies the role of financial shocks, and Justiniano et al. (2011) emphasizes the importance of investment-specific shocks empirically comoving with credit spreads. The notion that production of capital involves time relates to the concept of roundabout methods of production introduced by von Böhm-Bawerk (1891).
To fill this gap in the literature, I develop a general equilibrium model, which allows me to study the business cycle implications of countercyclical time to build. The model is an RBC model with specific capital. In my model specific capital means that investment is partially irreversible and that investment supply is subject to search frictions capturing time to build. In the model, longer time to build depresses real economic activity. This is primarily because a longer waiting time effectively injects uncertainty into the investing firm’s planning problem. In combination with partial investment irreversibility, higher uncertainty hampers an efficient allocation of capital across producers leading to adverse aggregate effects. In the calibrated model, time to build accounts for a third of the empirically observed drop in GDP and investment during the last two severe recessions.

To measure time to build, I use the US Census M3 survey of manufacturing firms. The Census provides publicly available time series for the order backlog and shipments of the non-defense equipment good sector since 1968. These time series allow me to estimate the average duration of a new order in a capital producer’s order book. Since shipments are highly persistent over time, a good approximation to the order duration is the order backlog ratio over shipments, which is my baseline time to build measure. The paper documents that time to build is countercyclical and exhibits substantial variation.

The model I develop is an RBC model featuring lumpy investment in line with the micro-level evidence on capital adjustment. The model explicitly distinguishes between capital supply and demand. On the capital demand side, firms face idiosyncratic productivity shocks and produce consumption goods using specific capital. To invest in specific capital, a consumption goods producer hires an engineering firm that devises a blueprint for the investment project. Using this blueprint, the engineering firm searches for a capital supplier that can produce the matching goods. The capital good market is frictional and match efficiency shocks, that capture turbulence on capital goods markets, cause fluctuations in time to build. Households that value consumption and leisure close the model.

\footnote{In fact, the specificity of capital is a standard explanation for the substantial order backlog producers of capital goods accumulate. Relatedly, capital good producing industries are typically classified as produce-to-order, distinguished from produce-to-stock industries, see Belsley (1969).}

\footnote{This paper is not the first in documenting the countercyclicality of the backlog ratio, but this paper is the first to relate the backlog ratio to time to build in the context of a modern, dynamic macroeconomic model. For example, recent work by Nalewaik and Pinto (2015) documents the backlog ratio to be countercyclical and studies its behavior over time using a model in the class of linear quadratic models, see Ramey and West (1999).}
Time to build affects the economy through a direct channel and an indirect channel. The direct channel is the mechanical decline in contemporaneous investments when match efficiency shocks lengthen waiting time. The indirect channel, which is quantitatively key, captures that longer time to build worsens the allocation of capital across firms. Misallocation increases because investment policies change in two respects, if firm-level productivity is persistent. First, firms adopt a *wait-and-see* policy. They tend to delay investments because higher time to build effectively increases the uncertainty about the profitability of the investment project. Second, if productivity is additionally mean-reverting, time to build induces a *regression-to-the-mean* effect. That is, the investment policy reacts less to contemporaneous deviations from the long-run productivity mean.

To solve the model, I adopt the Reiter (2009) algorithm, which combines global projection methods with local perturbation solution methods.

The calibration strategy is to jointly match the investment lumpiness observed in the micro data and the time series fluctuations in time to build. Movements in time to build are caused match efficiency shocks.

In the calibrated model, match efficiency shocks explain quantitatively important fluctuations. A shock that raises time to build by one month causes a sharp drop in investment of 2%, and a drop in output of up to 0.5%, albeit more gradual. I show that the direct channel is crucial for the short-term responses, while the indirect misallocation channel, explains nearly all of the medium-term responses. Misallocation effects, that are well captured by the endogenous decline in aggregate TFP, build up gradually because firm-level productivity is persistent.

To corroborate the quantitative results, I fit a medium-scale vector autoregression (VAR) model and identify match efficiency shocks using minimal theoretical assumptions. The VAR includes macroeconomic aggregates, prices, and time to build. The restrictions to identify structural match efficiency shocks are arguably conservative: the identified shock may contemporaneously only affect time to build. The VAR allows other structural shocks to explain movements in time to build. I find that adverse match efficiency shocks significantly and persistently lower GDP, investment, and consumption. The effects are quantitatively important and the identified shock explains more than 20% of the forecast error variance of GDP and consumption. The identified shocks are uncorrelated with other common business cycle shocks. Finally, I develop and apply a new robustness exercise for structural VAR models, where equality restrictions are relaxed by flexible elasticity bounds.
Related Literature

First, this paper contributes to the literature studying the macroeconomic implications of lumpy investment. There is ample evidence for investment lumpiness, see, for example, Doms and Dunne (1998), and structural explanations are investment irreversibilities or fixed capital adjustment, see, for example, Cooper and Haltiwanger (2006). In this paper, fixed capital adjustment are micro-founded and follow from overhead costs of engineers and capital suppliers. Recent work has investigated the macroeconomic implications of capital adjustment costs for the response to aggregate productivity shocks, see, for example, Khan and Thomas (2008) and Bachmann et al. (2013), and, for the response to uncertainty shocks, see, for example, Bloom (2009), Bachmann and Bayer (2013), and Bloom et al. (2014). In the present paper, the interaction between time to build and fixed capital adjustment costs is key for the transmission of match efficiency shocks in the capital goods market. The mechanism in the model resembles the real option effects of time-varying uncertainty, though without inducing the frequency effect often responsible for fast reversals and overshooting in models with uncertainty shocks. To the extent that longer time to build increases ‘effective’ uncertainty, this paper also contributes to the endogenous uncertainty literature, see, for example, Bachmann and Moscarini (2011) and Fajgelbaum et al. (2014).

Second, this paper relates to recent papers studying the interaction between time to build fluctuations and investment irreversibility. Studying time to build for residential housing, Oh and Yoon (2016) document a time series pattern fairly similar to the counter-cyclical time to build for capital goods documented in this paper. In their model, higher uncertainty increases time to build because residential construction occurs in stages and each stage involves irreversible investment. Kalouptsidi (2014) develops a model of the bulk shipping industry and shows that fluctuations in time to build dampen the volatility of investment. This stands in contrast to my paper, and the different conclusion is in part due to the existence of the misallocation channel in my model.

Third, in modeling a frictional market for intermediate capital goods I build on the large search literature. Ever since Mortensen and Pissarides (1994), search frictions are a popular explanation of unemployment. Studying search frictions on capital markets, instead, Kurmann and Petrosky-Nadeau (2007) and Ottonello (2015) provide models where search frictions prevent speedy reallocation of capital across firms and generate amplification. In these models, tightness on the capital goods market
governs the intensive margin of investments, while in my setup search frictions also affect the extensive margin of capital goods delivery. Match efficiency shocks in my model build on the labor market search and matching literature, where match efficiency shocks have been shown to play an important role to understand unemployment fluctuations, especially during severe recessions, see, for example, Krause et al. (2008), Sedláček (2014), and Sedláček (2016). An alternative interpretation of the match efficiency shocks in my model involves search for credit, as in Petrosky-Nadeau and Wasmer (2015).

Finally, most business cycle models in discrete time starting from the seminal Kydland and Prescott (1982) and including most New Keynesian literature as well, see, for example, Smets and Wouters (2007), feature constant time to build. The main motivation is to improve the model fit of the investment time series. In fact, Kydland and Prescott (1982) acknowledges that “important cyclical variation in the construction period would necessitate an alternative technology”. Adopting a less narrow definition of time to build, the present paper provides the evidence for important cyclical variation and suggests an alternative technology.

The remainder of this paper is organized as follows: Section 2 presents the empirical measure of time to build and documents its counter-cyclicality. In Section 3, I develop the business cycle model accounting for time to build fluctuations. The calibration strategy follows in Section 4 and the macroeconomic effects of countercyclical time to build are discussed in Section 5. Section 6 corroborates the macroeconomic implications identifying match efficiency shocks using a SVAR model. Finally, Section 7 discusses possible explanations of time to build fluctuations and concludes.

2. DOES TIME TO BUILD VARY OVER THE CYCLE?

This section suggests a measure for time to build based on survey data of capital good producer and documents its countercyclicality.

The primary data source is the US Census Manufacturers’ Shipments, Inventories, and Orders (M3) Survey. The M3 survey covers two thirds of companies with more than 500 million USD of annual sales and 50% of total manufacturing sales. Some smaller companies are included to improve industry coverage and the survey asks multi-sector firms to provide divisional reporting. In total, M3 contains about 3,000 companies and about 4,800 reporting units. These survey participants are selected from the Economic Census (EC) and the Annual Survey of Manufactures (ASM)
and M3 data is benchmarked against the EC and ASM. Among the primary usages of the M3 survey, the U.S. Bureau of Economic Analysis (BEA) uses capital good shipments to estimate quarterly fixed capital investments.

The goal is to estimate time to build faced by investing firms using survey data on the order books of capital good producers. Survey data is publicly available at the two-digit sector level and for some special categories. Under the premise of excluding defense goods, arguably the most appropriate sector category is non-defense equipment goods, available from 1968 through 2015. A caveat is that the M3 being a US manufacturing survey excludes structure capital and imported equipment capital, which together account for no more than 35% of total non-residential private fixed investments in the US.

The main idea behind measuring time to build is to estimate the average duration of a new order in a capital good producer’s order book. The M3 survey collects data on new orders net of cancellations \( O \), shipments \( S \), and the stock of order backlog \( B \) at monthly frequency. A new order is defined as a legally binding intention to buy for immediate or future delivery, and, unfortunately, the survey does not ask separately for order cancellations. Shipments measure the value of goods delivered in a given period, while order backlog measures the value of orders that have not yet fully passed through the sales account. New orders, shipments, and order backlog satisfy a stock-flow equation,

\[
B_t = B_{t-1} + O_t - S_t, \tag{2.1}
\]

where \( B_t \) denotes the end-of-period stock value, \( O_t \) and \( S_t \) the period flow values, respectively. The baseline measure of time to build

\[
TTB_t \equiv \frac{B_t}{S_t}, \tag{2.2}
\]

is the so-called backlog ratio, and measures the number of months a new order remains in a capital producer’s order book if shipments are expected to remain

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5Further information on the M3 survey can be found at www.census.gov/manufacturing/m3.
6Notice that for finer disaggregation of equipment goods into two-digit sectors, the distinction of defense and non-defense is not always given. For example data on the aircraft equipment sector is not available per defense and non-defense goods.
7Out of total private non-residential fixed investment, structure capital constitutes on average 25% over the last 40 years, declining over time with 10% in 2015. Imported equipment capital is on average 10% of total investments, increasing over time with 20% in 2015.
unchanged. The martingale condition is not strong because shipments \((S_t)\) are in fact highly persistent. An alternative measure for time to build measures the ex-post time an average order remains in a capital good producer’s order book,

\[
\tilde{TTB}_t \equiv \min_i \left( \sum_{j=1}^{\lfloor i \rfloor} S_{t+j} + (i - \lfloor i \rfloor)(S_{t+\lfloor i \rfloor+1} - S_{t+\lfloor i \rfloor}) - B_t \right)^2.
\]

Figure 1 shows the two time to build series from January 1968 through January 2015. Three findings stand out: First, the two time to build measures barely differ reflecting the high persistence in shipments. In the following, the paper will consider only the baseline measure. Second, time to build exhibits substantial time series variation. The average time between order and delivery fluctuates between 3 and 9 months. Third, time to build increases toward the end of economic expansions, reaches peak value within recession periods. Time to build is thus countercyclical. The countercyclicality of the ratio of order backlog to shipments has been documented before, see, e.g., Nalewaik and Pinto (2015).

The correlation of real GDP growth with log time to build is -30%. Further, the paper detrends time to build using the HP filter with a smoothing parameter of
MATTHIAS MEIER

810,000 to abstract from slow-moving trends. The implied correlation with GDP growth decreases to -40%. Decomposing the equipment good sector into two-digit SIC industries, the correlation with GDP growth is negative correlation for all industries. In particular, the correlation of the detrended logarithmized backlog ratio with real GDP growth is -30% for industrial machinery and equipment, -23% for electronic equipment, -37% for transportation equipment, and -18% for instruments. Among the 2-digit industries, the largest average time to build is observed for transportation equipment with about 5 months and the smallest for instruments with about 1.5 months.

3. MODELING CYCLICAL FLUCTUATIONS IN TIME TO BUILD

In this section I model cyclical fluctuations in time to build. My model builds upon the basic RBC model and extends the model in two ways. First, producers of consumption goods are heterogeneous: they vary in their productivity and use specific capital in production. Second, investments in specific capital are supplied through a frictional capital good market giving rise to time to build. Match efficiency shocks on this market lead to fluctuations in time to build. Otherwise, the model is an infinite-horizon, general equilibrium model in discrete time indexed by $t$ with aggregate uncertainty and complete asset markets.

3.1. Consumption good producers

The economy consists of a fixed unit mass of perfectly competitive consumption good firms, indexed by $j$, that produce a homogeneous consumption good

\begin{equation}
(3.1) \quad y_{jt} = z_t x_{jt} k_{jt}^{\alpha} \ell_{jt}^{\nu},
\end{equation}

using firm-specific capital, $k_{jt}$, labor, $\ell_{jt}$, and subject to aggregate productivity, $z_t$, and idiosyncratic productivity, $x_{jt}$. I assume the production function has decreasing returns to scale in the control variables: $0 < \alpha + \nu < 1$. Both idiosyncratic and aggregate productivity follow an AR(1) process in logs, respectively,

\begin{equation}
(3.2) \quad \log(z_t) = \rho^z \log(z_{t-1}) + \sigma^z \epsilon_{zt}^z, \quad \epsilon_{zt}^z \sim \mathcal{N}(0, 1),
\end{equation}

\begin{equation}
(3.3) \quad \log(x_{jt}) = \rho^x \log(x_{jt-1}) + \sigma^x \epsilon_{jt}^x, \quad \epsilon_{jt}^x \sim \mathcal{N}(0, 1).
\end{equation}
Firm-specific capital evolves over time by \( \gamma k_{jt+1} = (1-\delta)k_{jt} + i_{jt} \), where \( \delta \) denotes the depreciation rate, \( i_{jt} \) are investments, and \( \gamma \) denotes constant, aggregate growth of labor productivity. Notice that throughout the paper, the model is formulated along the balanced growth path. To invest in specific capital, consumption good producers sign an order contract with an engineering firm. In turn, the engineer develops a blueprint and searches for the required capital on a frictional capital goods market until the order is fulfilled. I assume that engineers can perfectly commit to an order and that consumption good producers can only hire one engineer for a given investment project.

As a result of search frictions, investment orders are not delivered instantaneously, but with probability \( q(m_t) \) implying average time to build of \( 1/q(m_t) \). The next subsection shows that delivery probability depends only on \( m_t \), the match efficiency shock. Further, investment entails a fixed adjustment cost, \( f_E^t(\xi_{jt}) \), with \( f_E^t \) strictly increasing in \( \xi_{jt} \), and \( \xi_{jt} \) random and iid across investment orders with cumulative distribution function \( G \). This fixed cost is micro-founded and also arises from the search market for capital goods explained in the next subsection. In addition, I assume re-adjusting an outstanding order before delivery is prohibitively costly. Finally, consistent with the notion of firm-specific capital, we assume resale losses of capital acting as a further adjustment friction.\(^8\)

In the dynamic firm problem, I distinguish between consumer good producers with and without outstanding orders. For firms without outstanding orders, the idiosyncratic state is described by \((k_{jt}, x_{jt}, \xi_{jt})\) and for firms with outstanding order, the idiosyncratic state consists of \((k_{jt}, k_{ojt}, x_{jt}, \xi_{jt})\), where \( k_{ojt} \) denotes next period’s capital stock if the outstanding order is delivered. I denote the cross-sectional distribution of consumption good firms over their idiosyncratic states by \( \mu_t \). The economy’s aggregate state is denoted by \( s_t = (\mu_t, z_t, m_t) \), see Section 3.4. In the following, I drop time and firm indices and use ‘ notation to indicate subsequent periods.

With frictionless labor adjustment, cash flow gross of capital expenditure is

\[
(3.4) \quad cf(k, x, s) = \max_{\ell \in \mathbb{R}_+} \left\{ z x k^\alpha \ell^\nu - w(s) l \right\},
\]

where \( w(s) \) denotes the wage rate. Firms discount future profits by the stochastic

\(^8\)I assume reselling is also subject to time to build: Disinvesting producers need to hire an engineer that searches for a capital supplier that transforms the capital into consumption goods.
discount factor \( Q(s, s') \). The value of a firm without outstanding order is given by

\[
V(k, x, \xi, s) = \max \left\{ V^A(k, x, \xi, s), V^{NA}(k, x, s) \right\}.
\]

(3.5)

Conditional on ordering investment goods, the firm value is

\[
V^A(k, x, \xi, s) = \max_{k^o \in \mathbb{R}_+} \left\{ W(k^o, x, \xi, s) \right\},
\]

(3.6)

and ordered investment goods are implicitly defined by

\[
i(k, k^o) = \gamma k^o - (1 - \delta)k.
\]

When disinvesting, the consumption good producer incurs a resale loss defined by

\[
p^s(k, k^o) = \begin{cases} \bar{p}^s & \text{if } i(k, k^o) < 0 \\ 1 & \text{else} \end{cases}
\]

where \( 0 \leq \bar{p}^s \leq 1 \). The value of the consumer good firm with outstanding orders is

\[
W(k^o, x, \xi, s) = cf(k, x, s) + q(s) \left[ -p^s(k, k^o)i(k, k^o) - Q(s', s') V\left(k^o, x', \xi', s'\right) | x, s \right] \\
+ (1 - q(s)) \left[ E\left[Q(s, s') W\left(k', k^o, x, \xi, s\right) | k, k^o, x, s \right] \right],
\]

\[
\text{s.t. } k' = (1 - \delta)k / \gamma \text{ and } k'^o = k^o - (1 - \delta) / \gamma (1 - (1 - \delta) / \gamma)k.
\]

Notice that I ensure that investments \( i(k, k^o) \) are unaffected by the realized waiting time by ‘depreciating’ state \( k^o \) while waiting for delivery. Finally, conditional on not adjusting, the firm value is

\[
V^{NA}(k, x, s) = cf(k, x, s) + E[Q(s, s') V(k', x', \xi', s') | x, k, s],
\]

(3.8)

\[
\text{s.t. } k' = (1 - \delta)k / \gamma.
\]

The extensive margin of the capital adjustment (ordering) decision is described by the threshold value \( \hat{\xi}(k, x, s) \) that satisfies

\[
V^A(k, x, \hat{\xi}(k, x, s), s) = V^{NA}(k, x, s).
\]

(3.9)

Adjustment is optimal whenever a random, fixed adjustment costs \( \xi < \hat{\xi}(k, x, s) \). Note that this formulation of the firm problem nests the conventional firm problem with one period time to build whenever \( q(s) = 1 \) \( \forall s \).
3.2. **Engineering firms and capital suppliers**

To invest in specific capital, consumption goods producers need to hire an engineering firms (in short engineers). In turn engineers hire labor to produce a blueprint and search for a capital goods producer that can supply the goods as required by the blueprint. This setup provides a theory of endogenous time to build fluctuations.

In detail, there is a continuum of capital good submarkets characterized by $\xi$ with distribution $G$, which consumption good producers randomly access. The remainder of this subsection focuses on an arbitrary submarket $\xi$. There is a large mass of engineer and capital suppliers. Let the number of active engineers be $E_t$, and of active capital suppliers $P_t$. Engineers and capital suppliers need to hire $\xi$ workers (overhead) to participate in the market. Workers are mobile across sectors so there is a single equilibrium wage. The number of engineers equals the number of orders because a consumption good producer can not hire more than one engineer. Engineering firms are hired on a spot market, they can perfectly commit and are perfectly competitive. Conditional on delivery, engineers receive compensation $f_E^t$ from consumption good producers. To deliver, the engineer needs to find a matching capital supplier subject to search frictions. When matched, capital goods are produced within the period. Capital suppliers produce using a one-to-one production technology transforming consumption goods into capital goods goods. The outstanding investment order is delivered at the end of the period. For analytic tractability, I assume matches are separated after transactions.

Formally, the number of matches between engineers and capital suppliers is given by the matching function

$$M_t = m_t E_t^{\eta} P_t^{1-\eta},$$

where stochastic match efficiency $m_t$ follows an AR(1) process in logs

$$\log(m_t) = (1 - \rho^m) \log(\mu^m) + \rho^m \log(m_{t-1}) + \sigma^m \epsilon^m_t, \quad \epsilon^m_t \sim N(0,1),$$

which captures turbulence in the capital goods market. I define market tightness as $\theta_t = E_t / P_t$ and the probability of filling an order for an engineer is given by

---

9The assumption of equal participation costs ($\xi$) is wlog. In equilibrium, costs differences only affect the steady state level of equilibrium tightness. Calibrating the model to match time to build would eliminate any differences in participation costs.

10Given the production technology of capital suppliers and the assumption of fixed production costs only, the relative unit price of capital expressed in consumption good units is one.
\( q(m_t, \theta_t) = m_t \theta_t^{-1} \). Conversely, the matching probability for a capital supplier is \( q(m_t, \theta_t) \theta_t \). If matched, engineers compensate capital goods producers by paying \( f_t^P \).

Denote by \( Q_{t,t+1} \) the stochastic discount factor (as in the consumption good firm problem), then the value of an unmatched and matched engineer is, respectively,

\[
V^E_t = - \xi w_t + q(m_t, \theta_t) J^E_t + [1 - q(m_t, \theta_t)] \mathbb{E}_t Q_{t,t+1} V^E_{t+1}^t, \quad J^E_t = f^E_t - f^P_t,
\]

and of an unmatched and matched capital goods producer, respectively,

\[
V^P_t = - \xi w_t + \theta_t q(m_t, \theta_t) J^P_t + [1 - \theta_t q(m_t, \theta_t)] \mathbb{E}_t Q_{t,t+1} V^P_{t+1}^t, \quad J^P_t = f^P_t.
\]

On this market, the value of an unmatched engineer is zero because engineers are perfectly competitive on the spot market for investment orders, \( V^E_t = 0 \). The value of unmatched capital goods producers is also zero because of free entry, \( V^P_t = 0 \).

I assume engineers and capital goods producers share the match surplus \( f^E_t \) by Nash-bargaining over compensation \( f^P_t \),

\[
\max_{f^P_t} (J^E_t - V^E_t) \phi (J^P_t - V^P_t)^{1-\phi}.
\]

The solution to Nash bargaining together with the zero profit and the free entry condition implies \( f^P_t = (1 - \phi) f^E_t \). This obtains equilibrium tightness

\[
\theta = \frac{\phi}{1 - \phi},
\]

which is constant over time and only depends on bargaining parameter \( \phi \). Thus adverse shocks to match efficiency \( m_t \) unambiguously decrease the probability that an engineer fills an order and thus raise time to build. It further follows from free entry and zero profits that the engineer’s compensation satisfies

\[
f^E(\xi, s) = \frac{\xi w(s)}{\phi q(s)}, \quad q(s) = m \theta^{-1},
\]

with wage and delivery probability re-expressed in terms of the aggregate state. The engineer compensation constitutes the fixed adjustment costs that consumption good producers incur when investing.
3.3. **Households**

Households value consumption and leisure. I assume separable preferences, which together with complete asset markets, implies the existence of a representative household. Assuming indivisible labor, see Hansen (1985) and Rogerson (1988), the utility function of the representative household is

\[ U(C, L) = \frac{C^{1-\sigma}}{1-\sigma} - \psi L, \]  

where \( C \) is consumption and \( L \) labor supply. \( \sigma \) denotes the intertemporal substitution elasticity, and \( \psi \) parametrizes the disutility of working. The household owns all firms and receives aggregate profits \( \Pi(s) \). The problem of the household problem is

\[ \max_{C,L} U(C, L) \quad \text{s.t.} \quad C \leq w(s)L + \Pi(s). \]  

Because of household ownership, firms use the stochastic discount factor

\[ Q(s, s') = \beta \frac{p(s')}{p(s)}, \]

which is the intertemporal marginal rate of substitution with \( p(s) = C(s)^{-\sigma} \) the marginal utility of consumption. The household’s optimal labor supply requires \( w(s) = \psi/p(s) \).

3.4. **Recursive Competitive Equilibrium (RCE)**

A RCE is a list of functions \((w, f^E, q, \ell, k^o, \xi, C, L, \Pi, Q, V, W, \mu')\) that satisfy:

(i) **Consumption good producers:** \((\ell, k^o, \xi, V, W)\) solve (3.4)–(3.9).

(ii) **Engineering firms and capital good producers:** \((f^E, q)\) satisfy (3.16).

(iii) **Household:** \((C, L)\) solve (3.18).

(iv) **Consistency:**

   (a) \( \Pi \) is consistent with profit maximization of consumption good firms.

   (b) \( Q \) is given by (3.19).

   (c) \( \mu' \), the law of motion of \( \mu \), is consistent with functions \((q, k^o, \xi)\).

(v) **Labor market clearing:** Supply \( L \) equals labor demand determined by \((\ell, \xi)\), and the distribution of \( \xi \).

(vi) **Goods market clearing:** \( C = Y - I \), with \( Y, I \) determined by \((q, \ell, k^o, \xi)\).

A more detailed version of this equilibrium definition is provided in the Appendix.
3.5. Solution

The recursive competitive equilibrium is not computable, because the solution depends on infinite-dimensional distribution $\mu$. Instead, I solve for an approximative equilibrium using perturbation methods building on the seminal work in Reiter (2009). The general idea is to use global approximation methods with respect to the individual states, but local approximation methods for the aggregate states. I solve for the steady state using projection methods and perturb the model locally around the steady state to solve for the model dynamics in response to aggregate shocks.

Compared to the algorithm developed in Krusell et al. (1998), the perturbation approach does not require simulating the model with respect to aggregate shocks (in order to update the parameters of the forecasting rules), neither does it suffer from the curse of dimensionality with respect to the number of aggregate shocks. These differences have implications for computational time. As shown in Terry (2015) for the Khan and Thomas (2008) economy, the Reiter algorithm is more than 100 times faster than the Krusell-Smith algorithm. In addition, Reiter (2016) shows that the Reiter algorithm is equivalent to a linear Krusell-Smith algorithm. In light of these advantages it is not surprising that the Reiter algorithm is becoming increasingly popular. For example, Ahn et al. (2016) combine the Reiter algorithm to compute aggregate dynamics for a general class of heterogeneous agent economies in continuous time. More closely related to this paper, Winberry (2016a) uses (and extends) the Reiter algorithm to solve a Khan and Thomas (2008) economy.

My adaption of the Reiter method uses cubic B-splines with collocation to approximate the value functions. For the model as calibrated in the next section, it takes 1 minute to solve the steady state, aggregate dynamics, and compute the impulse response functions. Appendix A contains details on the solution method.

4. Calibration

In this section, I discuss the calibration of my model, which broadly follows the literature on general equilibrium models with non-convex capital adjustment frictions, see, e.g., Khan and Thomas (2008).

I calibrate the model at quarterly frequency. To match an annual risk-free rate of 4%, I set the discount factor $\beta = 0.99$. I assume log-utility in consumption, and the parameter governing the disutility of labor, $\psi$, is calibrated to match a share of time spent working of one third.
TABLE I
QUARTERLY MODEL CALIBRATION

<table>
<thead>
<tr>
<th>Description</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Consumption good producers</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capital share</td>
<td>$\alpha$</td>
<td>0.250</td>
</tr>
<tr>
<td>Labor share</td>
<td>$\nu$</td>
<td>0.580</td>
</tr>
<tr>
<td>Depreciation rate</td>
<td>$\delta$</td>
<td>0.025</td>
</tr>
<tr>
<td>Aggregate growth</td>
<td>$\gamma$</td>
<td>1.004</td>
</tr>
<tr>
<td>Idiosyncratic persistence</td>
<td>$\rho^x$</td>
<td>0.970</td>
</tr>
<tr>
<td>Idiosyncratic dispersion</td>
<td>$\sigma^x$</td>
<td>0.065</td>
</tr>
<tr>
<td>Aggregate persistence</td>
<td>$\rho^z$</td>
<td>0.950</td>
</tr>
<tr>
<td>Aggregate dispersion</td>
<td>$\sigma^z$</td>
<td>0.007</td>
</tr>
<tr>
<td>Fixed adjustment cost</td>
<td>$\xi$</td>
<td>0.010</td>
</tr>
<tr>
<td>Resale loss</td>
<td>$\bar{p}_s$</td>
<td>0.830</td>
</tr>
<tr>
<td><strong>Engineers and capital suppliers</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bargaining power</td>
<td>$\phi$</td>
<td>0.500</td>
</tr>
<tr>
<td>Matching function elasticity</td>
<td>$\eta$</td>
<td>0.500</td>
</tr>
<tr>
<td>Mean matching efficiency</td>
<td>$\mu^m$</td>
<td>0.542</td>
</tr>
<tr>
<td>Persistence of matching efficiency</td>
<td>$\rho^m$</td>
<td>0.959</td>
</tr>
<tr>
<td>Dispersion of matching efficiency</td>
<td>$\sigma^m$</td>
<td>0.041</td>
</tr>
<tr>
<td><strong>Households</strong></td>
<td></td>
<td></td>
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<tr>
<td>Discount factor</td>
<td>$\beta$</td>
<td>0.990</td>
</tr>
<tr>
<td>Intertemporal elasticity</td>
<td>$\sigma$</td>
<td>1.000</td>
</tr>
<tr>
<td>Preference for leisure</td>
<td>$\psi$</td>
<td>2.400</td>
</tr>
</tbody>
</table>

The output elasticities describing the Cobb-Douglas production technology are set to $\alpha = 0.25$ and $\nu = 0.58$. These values for $\alpha$ and $\nu$ are well within the range of estimates in Cooper and Haltiwanger (2006) and Kehrig (2015), and very similar to the ones used in Khan and Thomas (2008) and Bachmann et al. (2013). Interpreting the production function as revenue production function composed of a demand curve and a CRS physical technology, the value for output elasticities imply a markup of roughly 20%. I assume $\delta = 0.025$ consistent with an annual depreciation rate of 10%. Following Khan and Thomas (2008), I calibrate to an annualized aggregate productivity growth of 1.6%.

I assume the distribution $G$ of fixed adjustment costs $\xi$ is uniform with lower bound zero and upper bound $\bar{\xi}$. To calibrate $\bar{\xi}$ and resale loss $\bar{p}_s$, I target the tails
of the investment rate distribution. Notice that both the adjustment costs, and the idiosyncratic productivity process, described by $\rho^x$ and $\sigma^x$, are crucial determinants of the investment rate distribution. It is therefore key to calibrate these parameters jointly the same dataset. In addition, aggregation matters for the investment rate distribution: Plant-level lumpiness may be hardly visible in a dataset of large firms operating several plants. This paper calibrates the parameters of idiosyncratic productivity and adjustment costs using the LRD establishment-level data.\footnote{Alternative data sources used to calibrate and estimate similar models are the IRS tax data, see, e.g., Winberry (2016b), and Compustat data, see, e.g., Bloom (2009). Both datasets are at the firm-level. The IRS does include only positive investments, and Compustat is biased to large private firms. The main disadvantage of the LRD dataset is that it covers manufacturing only.}

I calibrate the idiosyncratic profitability process to have persistence $\rho^x = 0.97$ and standard deviation of $\sigma^x = 0.065$. Notice that Cooper and Haltiwanger (2006) estimate the production technology $\tilde{x}k^\theta$, which I take as the production technology after maximizing out labor with $\theta = \alpha/(1 - \nu)$. Given $\nu$, I translate their estimates of the profitability process at annual frequency into the parameters describing the quarterly process of $x$, where $x = \tilde{x}^{1-\nu}$. To calibrate adjustment cost parameters $\tilde{\xi}$ and $\tilde{\rho}$ I target the share of positive and negative spike adjusters, documented in Cooper and Haltiwanger (2006). The two model parameters can exactly match the 18.6% share of positive spikes and the 1.5% share of negative spikes. The fixed cost is important to generate fat tails, while the resale loss is particularly important in generating the large difference between positive and negative spikes.

In estimating capital adjustment costs, Cooper and Haltiwanger (2006) also targets the persistence of investment rates and the correlation of investment rates with idiosyncratic productivity. I exclude them because they may depend sensitively on the time to build setup. Nonetheless, the model matches these moments reasonably well with a persistence of 1.6% (empirically 5.8%), and a productivity correlation of 24% (empirically 14%).

An alternative strategy to calibrate adjustment costs is to target cross-sectional skewness and kurtosis of investment rates, see Bachmann and Bayer (2013). In fact, our calibrated model closely matches these moments in the data: skewness/kurtosis in the model are 5.1/48.3, while in a balanced panel of Census data these are 6.5/67.4 for total investment and 5.5/47.9 for equipment investment, see Kehrig and Vincent (2016). Since skewness and kurtosis monotonically increase in the adjustment cost parameters, this indicates the calibrated adjustment costs may be too low.

I assume symmetric Nash bargaining on capital good markets, $\phi = 0.5$. To satisfy
the efficiency condition in Hosios (1990), I set the elasticity of the matching function with respect to active engineers to $\eta = 0.5$. Under these two assumptions, delivery probability becomes $q_t = m_t$, and the exogenous process for matching efficiency is calibrated directly from the empirical measure of time to build. I set the mean matching efficiency to satisfy an average time to build of 5.5 months corresponding to the mean of the backlog ratio. Given that the backlog ratio has some small and non-linear time trends, I detrend the monthly time series using the HP filter with a low smoothing parameter of 8,100,000 and fit persistence and standard deviations to the residual from trend. Translating the monthly auto-correlation into a quarterly one, I obtain $\rho^m = 0.959$ and $\sigma^m = 0.041$.

5. MACROECONOMIC EFFECTS OF MATCH EFFICIENCY SHOCKS

In this section, I first discuss how match efficiency shocks affect the consumption good firm problem through time to build. Second, I present the results of the quantitative general equilibrium model and discuss the transmission channels.

5.1. **Time to build and the planning problem**

Two key determinants of a firm’s investment decision are expected future productivity and (forecast) uncertainty of future productivity. The larger expected future productivity, the more firms invest. If uncertainty of future productivity increases, the firm may prefer to postpone investments. To understand the effects of time to build in my model, it is key that time to build shifts the effective planning horizon for an investment project. When assessing a potential investment project, what matter are the expectations about profitability during the period the investment is expected to be used. This period shifts into the future as time to build increases. If firm productivity follows a persistent, mean-reverting process, fluctuations in time to build affect both expected productivity during the usage period and the uncertainty about productivity during the same time period.

To illustrate the argument, Figure 2 plots productivity forecasts (blue, sold line) and the associated confidence interval (blue, shaded area) as a function of the forecast horizon. The two vertical, dotted lines indicate time to build of 1 and 3 quarters, respectively. Expected productivity falls in the delivery period, while the confidence interval widens substantially.
What are the implications for a firm’s investment policy? First, the larger time to build, the less investments responds to contemporaneous deviation of productivity from its long run mean. This follows directly from mean reversion, and I refer to this change in the (intensive margin) investment policy as *regression-to-the-mean* effect. Second, higher time to build increases the uncertainty about productivity in the period of delivery, and thereafter. Given partial investment irreversibilities, the option value of waiting increases and the firm tolerates larger deviations of the current capital stock from its optimal size. In turn, the adjustment frequency falls and I refer to this change in the (extensive margin) investment policy as *wait-and-see* effect.\(^\text{12}\) If productivity shocks are permanent, instead, there is no regression-to-the-mean effect, but forecast uncertainty increases by more – linearly in the forecast horizon –, which strengthens the wait-and-see effect.

\(^{12}\)The wait-and-see effect is prominent in the uncertainty literature, see, e.g., Bloom (2009) and Bachmann et al. (2013). In my model, however, uncertainty is not exogenous, but driven by the forecast horizon. Relatedly, there is no volatility effect in my model which is a consequence of exogenous uncertainty shocks and leads to medium-run overshoot, see Bloom (2009).
5.2. Quantitative impact of time to build fluctuations

I evaluate the quantitative impact of match efficiency shocks in general equilibrium. Accounting for general equilibrium effects is important, because household consumption smoothing motives may substantially dampen the investment and output responses arising in partial equilibrium, see Khan and Thomas (2008).

Adverse match efficiency shocks depresses the macroeconomy by lengthening the time to build of investment orders. Real economic activity is affected through two channels, a direct channel and an indirect channel.

As for the direct channel, longer delivery times directly lowers investment. In a simple example with deterministic delivery, suppose delivery time shifts from 1 to 2 quarters. Then on impact no investment goods are delivered and investment falls to zero. In my model, time to build is stochastic at the firm-level and lower matching efficiency decreases the delivery probability. Similarly, the effects should be rather short-lived. First, the stock of outstanding orders increases when delivery probability is persistently lower which by itself mitigates the drop in investment. Second, investing firms adjust by preponing orders, increasing the stock of outstanding orders by even more.

The indirect channel operates through misallocation. This is for three reasons. First, as a direct consequence of longer time to build, previously ordered capital goods arrive later, which worsens the alignment of firm-level capital and productivity. Second, adoption of wait-and-see policies imply a lower adjustment frequency and thus more misallocation. Third, regression-to-the-mean increases misallocation as investment becomes less related to contemporaneous firm productivity. More misallocation manifests itself as lower aggregate TFP, which decreases output and consumption.

Figure 3 shows the responses to a match efficiency shock that increases time to build by one month. The size of the shock corresponds to one standard deviation in the filtered time to build time series. The shock explains substantial fluctuations in output, investment, and consumption. Investment is the most directly affected by the match efficiency shocks. It falls by 2% on impact and remains strongly depressed during the first two years after the shock hits the economy. Output falls by 30 basis points on impact and reaches its trough at 50 basis points five quarters later and dissipates slowly, with about half of the maximal effect remaining six years later.

To disentangle the two transmission channels, I estimate the direct effect by backward-engineering a series of aggregate productivity ($z$) shocks, which compen-
Figure 3: Responses to an adverse match efficiency shock

Notes: The impulse response functions are based on a decrease in match efficiency by one (unconditional) standard deviations starting from steady state and using the baseline calibration. ‘Direct effect’ are the impulse responses when aggregate TFP changes are eliminated through opposing aggregate productivity (z) shocks. Aggregate TFP is computed as $\text{TFP} = \log(Y_t) - \alpha \log(K_t) - \nu \log(L_t)$.

Sate the effect of the match efficiency shock on aggregate TFP. The resulting impulse responses are shown as dotted lines in Figure 3. Note that this exercise is an approximation at best because agents still expect lower future aggregate TFP under
the direct effect counterfactual. Taking this caveat into account means the direct effect is an upper bound to the true direct effect of a match efficiency shock. The figure shows that the direct effect is key to understand the immediate responses (first three quarters), while the medium-term effect is by and large explained by the indirect effect operating through misallocation.

Note that on impact of the shock, the share of consumption good producers making new investment orders increases. Hence wait-and-see effects are not dominant on impact. That is because firms prepone orders as delivery takes longer, see Figure 7 in Appendix B. Abstracting from the on-impact effect, however, the figure reconfirms wait-and-see behavior.

Further note that lower investment demand needs to correspond to lower production and/or higher consumption to clear the final good market. A typical RBC model feature is that because output is partly predetermined, the decrease in investment leads to an increase in consumption, see, e.g., Bloom et al. (2014). This stands in contrast with empirical business cycle co-movement, and we could introduce habits in consumption as in Winberry (2016a) to restore co-movement.

A possible concern with the model results may be the fact that fixed adjustment costs move directly in the delivery probability \( q \). As robustness for the results in Figure 3, I assume away these direct effects. Figure 8 in the Appendix shows that the responses are somewhat weaker, especially for aggregate investment, but the effects remain quantitatively important.

While the responses in Figure 3 show quantitatively seizable and highly persistent effects of match efficiency shocks, let me now assess the importance of time to build in understanding past business cycles. In particular, I estimate the match efficiency shock series to fit the empirical time to build measure. This confines my analysis to the period from 1968 through 2015. Using the model, I compute the time series for output, investment, consumption, and employment. To be sure, these time series are fluctuations induced only by match efficiency shocks. To make the time series comparable to the data, I HP filter both the simulated series and their empirical counterparts using the same low-frequency filter (HP with \( \lambda = 100,000 \)) I use for the calibration of match efficiency shocks. More details on the empirical time series are provided in Section 6.

Figure 4 compares the model-implied time series with their empirical counterparts. For better comparability I scale up the model-implied fluctuations by a factor of 4 (left scale) compared to the empirical fluctuations (right scale). Two observations
stand out. First, the official recessions periods (grey-shaded areas) are matched quite well by the match efficiency shocks. Second, match efficiency shocks explain an important share of the observed business cycle variations. This shock alone explains a drop in investments of more than 5% during the Great Recession and the early 1990s recession, compared to a drop of 16% in the data. For output, the model also explains more than a third of the empirically observed drop during these two recessions and for consumption it is almost a quarter.

Figure 4: Role of time to build in understanding past business cycles

Notes: These time series are computed matching the empirically observed (filtered) movements in time to build through match efficiency shocks and otherwise using the baseline model calibration. Grey-shaded areas indicate NBER recession dates.

6. TIME SERIES EVIDENCE ON MATCH EFFICIENCY SHOCKS

In this section, I corroborate the quantitative findings of the general equilibrium model in an empirical framework imposes minimal theory on the data. In particular, I identify match efficiency shocks in a structural VAR model.
I estimate a medium-scale VAR model that allows for rich dynamic interactions between time to build, as measured by the backlog ratio in Section 2, and several macroeconomic time series, prominent in both structural and empirical business cycle models. The vector of endogenous variables is:

\[
Y = \begin{bmatrix}
\text{Backlog Ratio} \\
\text{Real GDP} \\
\text{Real Consumption} \\
\text{Real Investment} \\
\text{Consumer Prices} \\
\text{Real Wage} \\
\text{Federal Funds Rate} \\
\text{Labor Productivity}
\end{bmatrix}
\]

The data used is at quarterly frequency covering from 1968Q1 through 2014Q4 and all macroeconomic time series except the backlog ratio are sourced from FRED.\textsuperscript{13} Labor productivity is real GDP over employment.

Notice that I use non-durable consumption goods, because durable consumption goods include equipment goods that may be directly affected by match efficiency shocks, while any response in non-durable consumption goods should mainly reflect general equilibrium responses. Similarly, my preferred investment time series is nonresidential investments because the backlog ratio does not relate to structures.

The baseline structural VAR model is in levels and includes a linear time trend

\[
Y_t = A_0 + D_t + \sum_{j=1}^{4} A_j Y_{t-j} + B u_t, \quad \text{Cov}(u_t) = I_8, \quad BB' = \Sigma,
\]

where \(u_t\) denotes the vector of structural shocks and \(\Sigma\) is the covariance matrix of reduced-form shocks \(B u_t\). W.l.o.g., I assume the match efficiency shock is the first element in vector \(u_t\). Thus the structural impulse responses of \(Y_t\) to the match efficiency shock are identified by the first vector in \(B\), denoted \(B_1\).

\textsuperscript{13}The FRED series names are GDPC96 (\textit{Real GDP}), DNDGRA3Q086SBEA (\textit{Real Personal Consumption Expenditures: Nondurable goods}), B008RA3Q086SBEA (\textit{Real Private Fixed Investment: Nonresidential}), CPI, AHETPI/CPI (\textit{Average Hourly Earnings of Production and Nonsupervisory Employees: Total Private; deflated by CPI}), FEDFUNDS (\textit{Effective Federal Funds Rate}), PAYEMS (\textit{All Employees: Total Nonfarm Payrolls}).
6.1. A conservative identification scheme

The baseline identification assumption is that the backlog ratio increases in response to an adverse match efficiency shock while all other macroeconomic time series do not respond contemporaneously, i.e. $B_1 = [b_{11}, 0, \ldots, 0]'$. Combining this identification restriction with $BB' = \Sigma$, it follows that $b_{11} = \sqrt{e_1'\Sigma^{-1}e_1}$, where $e_i$ is the i-th column of the identity matrix $I_8$. Thus, $B_1$ is point-identified by the identification restriction.

This identification scheme is conservative in the following sense. While, all other (not explicitly identified) structural shocks may affect the backlog ratio contemporaneously, the match efficiency shock may affect, e.g., GDP only through a one-quarter lag. This strategy resembles the identification of monetary policy shocks in Christiano et al. (2005).

Figure 5: Baseline impulse responses to an adverse match efficiency shock

Notes: Solid, blue lines show (selected) responses to a match efficiency shock, under the baseline identification scheme. Shaded, gray areas illustrate the associated 90% confidence intervals.

Figure 5 shows the IRFs to an adverse match efficiency shock that raises the backlog ratio by one conditional standard deviation above trend. The shock has a persistent, significant effect on the backlog ratio. More interestingly, GDP, and its two main components, investment and consumption, significantly fall in response to
the match efficiency shock. Not only are the responses statistically significant, but their magnitudes are also economically relevant: GDP and consumption fall by up to 0.5%, and investment by up to 1.5% within the first three years.

Table II shows the shares of forecast error variance explained by the match efficiency shock. The (conservatively identified) match efficiency shock explains an important fraction of macroeconomic fluctuations: more than 20% of GDP and consumption, and 7% of investment, variances along the trend. This provides further evidence in support of this paper’s suggestion that time to build fluctuations are important for a better understanding of business cycle fluctuations.

### Table II

**Forecast error variance decomposition**

<table>
<thead>
<tr>
<th></th>
<th>1 year</th>
<th>2 years</th>
<th>3 years</th>
<th>4 years</th>
<th>5 years</th>
<th>∞</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td>0.2</td>
<td>7.6</td>
<td>18.1</td>
<td>22.6</td>
<td>23.4</td>
<td>18.2</td>
</tr>
<tr>
<td>Investment</td>
<td>0.3</td>
<td>0.9</td>
<td>2.8</td>
<td>4.9</td>
<td>6.6</td>
<td>6.7</td>
</tr>
<tr>
<td>Consumption</td>
<td>0.8</td>
<td>9.8</td>
<td>22.2</td>
<td>26.9</td>
<td>28.2</td>
<td>24.6</td>
</tr>
<tr>
<td>Backlog ratio</td>
<td>73.4</td>
<td>57.0</td>
<td>48.8</td>
<td>44.8</td>
<td>42.2</td>
<td>31.1</td>
</tr>
</tbody>
</table>

Note: The shares of forecast error variance explained by match efficiency shocks are expressed as percentages for different forecast horizons ranging from 1 year to infinity.

### 6.2. Elasticity bounds

This paper proposes a new approach to providing robustness for point-identified structural VAR models in a frequentist setup. Structural VAR models, such as Gali (1999), Christiano et al. (2005), and Bloom (2009), impose various zero restrictions on contemporaneous and long-run responses to obtain point identification. As robustness, I propose to replace some or all of the zero restrictions by bounds on the elasticity with respect to the shock of interest. For example, instead of assuming an uncertainty shock does not contemporaneously affect GDP, as robustness I would restrict the elasticity of GDP with respect to a change in uncertainty due to an uncertainty shock to be bounded between $\pm c\%$. This nests the point-identified model in the limit case when all bounds are zero ($c = 0$). The structural VAR model is no longer point-identified when replacing a zero restriction with strictly positive bounds on the elasticities ($c > 0$).

---

14Elasticity bounds have recently gained popularity in the Bayesian structural VAR literature, see, e.g., Kilian and Murphy (2012) and Baumeister and Hamilton (2015).
I implement this robustness exercise using the results in Gafarov et al. (2016), which provide inference for set-identified structural VAR models. Formally, to apply their results, I need to assume that for a given IRF either the lower and upper elasticity bound may not hold jointly. Notice that confidence sets are estimated based on Delta method inference. In fact, bootstrap inference is not necessarily valid here because the endpoints of the identified sets are not fully differentiable.

The suggested robustness is similar to Conley et al. (2012) which proposes as robustness to relax the exclusion restriction when using IV methods. I suggest the following robustness for the conservative baseline identification. Instead of zero restrictions on contemporaneous responses, I constrain the elasticity of all variables (except for the backlog ratio) with respect to the match efficiency shock to be between -1% and +1%, see Table III. For an increase in the backlog ratio of 2.5%, the contemporaneous responses are bound to be between -0.025% and +0.025%.

**Table III**

<table>
<thead>
<tr>
<th>Identification schemes: constraints on contemporaneous elasticities</th>
</tr>
</thead>
<tbody>
<tr>
<td>TTB GDP Con Inv CPI Wag FFR LaP</td>
</tr>
<tr>
<td><strong>Baseline</strong></td>
</tr>
<tr>
<td><strong>Robustness</strong></td>
</tr>
</tbody>
</table>

Notes: +/0/±1% indicate that the elasticity is constrained to be positive/exactly zero/between -1% and +1%, respectively. The contemporaneous elasticity of variable i and the backlog ratio in response to match efficiency shocks is given by \( (e_i' B_1)/(e_1' B_1) \), where \( e_i \) is the i-th column of the identity matrix \( I_8 \). TTB: Backlog Ratio, GDP: Real GDP, Con: Real Consumption, Inv: Real Investment, CPI: Consumer Prices, Wag: Real Wage, FFR: Federal Funds Rate, LaP: Labor Productivity.

Figure 6 shows the resulting impulse responses under the robustness identification scheme. Instead of a single impulse response, there is an interval with admissible impulse responses (dotted lines). The confidence set is adjusted accordingly based on Gafarov et al. (2016). Notice that the main findings of the baseline model in Figure 5 are ‘robust’ in the sense that the declines in GDP, investment, and consumption remain significant.

6.3. **Additional robustness**

Appendix C provides additional robustness and empirical results. I evaluate the importance of the linear time trend by estimating the VAR under the same iden-
Figure 6: Robustness impulse responses to an adverse match efficiency shock

Notes: Solid, blue lines show (selected) responses to a match efficiency shock under the baseline identification scheme. Dotted, blue lines show the identified set under bounds on the elasticities, see Table III. Shaded, gray areas illustrate the 90% confidence intervals for the identified sets.

tification restrictions first differencing all variables. The results are broadly robust. Within the first three years, GDP, investment, and consumption respond significantly to a match efficiency shocks, and the magnitudes are similar to the baseline model in levels. Further, the results remain robust under the robustness identification scheme. I study whether the shock may actually capture another conventional business cycle shock. In Table IV, I correlate the identified match efficiency shock with various widespread measures of business cycle shocks, such as TFP shocks, monetary policy shocks and fiscal shocks. The match efficiency shock appears orthogonal to all shock measures investigated.

Beyond the robustness in Appendix C, the results are robust against switching to a monthly VAR replacing GDP by IP and investment by new orders for non-defense capital goods. Further, identification seems not to stem solely from the Great Recession as the VAR results when cutting the sample after 2008 suggest.
7. CONCLUSIONS

This paper suggests an empirical measure of time to build and documents its countercyclicality. To understand the transmission mechanism on real economic outcomes, I develop a new model with two key features: endogenous time to build driven by match efficiency shocks, and non-convex capital adjustment costs. Through the lens of the model, time to build affects the economy through both a direct effect on investment and an indirect misallocation effect. The latter is driven by changes in the investment policy which features wait-and-see and regression-to-the-mean effects when time to build is long. These induce capital misallocation, which in turn lowers aggregate TFP. The match efficiency shock explains quantitatively important fluctuations in output, investment, and consumption. In particular, these shocks explain more than a third of the drop in output and consumption during the Great Recession. Identifying match efficiency shocks in a VAR framework using minimal theory provides corroborating evidence.

An important follow-up question is: ‘What explains the match efficiency (time to build) fluctuations?’ From a theoretical viewpoint, a candidate explanation is countercyclical tightness in financial conditions. For example, with capital suppliers producing subject to cash-in-advance constraints and short-run liquidity becoming scarce during recessions, these suppliers may decide to slow down production despite long order books. Another candidate explanation is countercyclical firm exit (obviously not unrelated to financial conditions), which both destroys existing business relationship and makes it harder to establish new ones.

A more empirical angle to approach the question of what drives match efficiency, is to notice that the intensity of time to build fluctuations in different recessions. Time to build fluctuates the most during the early 1990s recession and the Great Recession, both of which are typically classified as financial recessions, whereas the Dot-Com Collapse of 2000 and preceding recession are less clearly financial recessions, see, e.g., Romer and Romer (2015). The timing of large time to build fluctuations thus lends support to financial conditions playing an important role.

When zooming out and focusing less on individual recessions, it becomes apparent that time to build has become more volatile since the mid-1980s. In fact, the period from the mid-1980s until 2007 is called the Great Moderation, which is characterized by less volatile business cycles. One popular explanation of the decline in volatility is ‘just-in-time’ inventory practices, which mitigates inventory volatility. Possibly, the flip side of lower inventory volatility is large time to build volatility.
Future research may investigate both the interplay between time to build and financial conditions, and the interplay between inventories and order backlog in order to shed more light on these open questions.

REFERENCES


TIMEx TO BUILD AND THE BUSINESS CYCLE


APPENDIX
In turn, this allows us to simplify the firm problem as

$$V_t(k, x, \xi) = p_t \mathbb{E}_x \mathbb{E}_\xi V_t(k, x', \xi'), \quad \tilde{V}_t^{A}(k, x, \xi) = p_t V_t^A(k, x, \xi), \quad \tilde{V}_t^{NA}(k, x) = p_t V_t^{NA}(k, x),$$

where \( \mathbb{E}_x \) (\( \mathbb{E}_\xi \)) denotes the expectation with respect to aggregate state \( s_t \) (\( \xi_t \)) conditional on \( s_t \). The net present value of adjustment costs can be expressed by \( ac_t \xi_t \), where \( ac_t \) is defined recursively as

$$ac_t = q_t p_t \frac{w_t}{\phi_q} + (1-q_t) \beta \mathbb{E}_t ac_{t+1}.$$

In turn, this allows us to simplify the firm problem as

$$V_t(k, x') = \mathbb{E}_x \mathbb{E}_\xi \max \left\{ \tilde{V}_t^{A}(k, x') - ac_t \xi_t', \tilde{V}_t^{NA}(k, x') \right\}$$

$$ac_t = q_t p_t \frac{w_t}{\phi_q} + (1-q_t) \beta \mathbb{E}_t ac_{t+1}$$

$$\tilde{V}_t^{A}(k, x) = \max_{k_t' \in \mathbb{R}^+} \left\{ \tilde{W}_t(k, k_t', x) \right\}$$

$$\tilde{W}_t(k, k_t', x) = p_t c f_t(k, x)$$

$$+ q_t \left[ p_t [-p^s(k, k_t')i(k, k_t')] + \beta \mathbb{E}_t \left[ \tilde{W}_{t+1}(k_t', x) \right] \right]$$

$$+ (1-q_t) \left[ \beta \mathbb{E}_t \left[ \tilde{W}_{t+1}((1-\delta)k/\gamma, k_t' - (1-\delta)/\gamma k_t' k_t', x) \right] \right]$$

$$\tilde{W}_t(k, k_t', x) = \mathbb{E}_x \tilde{W}_t(k, x')$$

$$\tilde{V}_t^{NA}(k, x) = p_t c f_t(k, x) + \beta \mathbb{E}_t \left[ \tilde{W}_{t+1}((1-\delta)k/\gamma, x) \right]$$
Importantly, this allows us to compute the extensive margin adjustment policy in closed form,

\[ \hat{\xi}_t = \hat{V}_t^A(k, x') - \hat{V}_t^{NA}(k, x') \frac{ac_t}{ac_t}. \]

Next, I approximate firm values using collocation where \( \Phi \) denotes basis functions in matrix representation and \( c \) denotes vectors of coefficients

\[
\hat{V}_t(k, x) \simeq \Phi^V(k, x)c_t^V \\
\hat{W}_t(k, k^o, x) \simeq \Phi^W(k, k^o, x)c_t^W
\]

The approximations are exact at the \( n_k \) collocation nodes \( k_1, ..., k_{n_k} \) and \( k^o_1, ..., k^o_{n_k} \). In practice, I choose the same collocation nodes for \( k \) and \( k^o \).

As baseline we use cubic B-splines to approximate the firm value functions. This does not only have the advantage of being computationally fast, but also conditional on the coefficients we know the Jacobian in closed form. In particular, we can write down the optimality condition for intensive margin capital adjustment \((k^o_t)\) as

\[
q_t \mu_t^p(k, k^o_t)\gamma = q_t \beta E_t \Phi^V(k^o_t, x)c_{t+1}^V + (1 - q_t) \beta E_t \Phi^W((1 - \delta)k_{t+1}/\gamma, k^o_t, x)c_{t+1}^W,
\]

where \( \Phi^V = (\partial \Phi^V)/(\partial k) \) and \( \Phi^W = (\partial \Phi^W)/(\partial k^o) \).

I approximate the AR(1) process of idiosyncratic productivity using Tauchen’s algorithm. I denote the discrete grid points of \( x \) by \( x_1, ..., x_{n_x} \) consisting of \( n_x \) grid points and the transition probability from state \( x_j \) to state \( x_{j'} \) one period later by \( \pi(x_{j'}|x_j) \).

To render the infinite-dimensional distribution \( \mu_t \) tractable, I approximate it with a discrete histogram. That is, \( \mu_t \) measures the share of firms for each discrete combination of capital stock \( k_i \), outstanding order \( k^o_i \) (both correspond to the collocation nodes), and productivity \( x_j \). A further distinction is useful: Let \( \mu^V_t \) denote the cross-sectional distribution of firms without outstanding orders over idiosyncratic states \((k_i, x_j)\) and \( \mu^W_t \) the distribution of firms with outstanding orders over \((k_i, k^o_i, x_j)\). It holds that \( \mu_t = (\mu^V_t, \mu^W_t) \).
Using the preceding approximation and simplification steps, the model equilibrium is described by the following non-linear equations:

\begin{align}
\Phi^V(k, x) c^V_t &= \mathbb{E}_x \mathbb{E}_\xi \max \left\{ V_t^A(k, x'), -ac_t \xi, V_t^{NA}(k, x') \right\} \\
\dot{z}_t(k, x) &= \left( V_t^A(k, x) - V_t^{NA}(k, x) \right) / ac_t \\
V_t^{NA}(k, x) &= p_c cf_s(k, x) + \beta E_t \Phi^V((1 - \delta)k/\gamma, x)c_{t+1}^{V} \\
V_t^A(k, x) &= \max_{k_t' \in \mathbb{R}^+} \left\{ W_t(k, k_t', x) \right\} \\
W_t(k, k_t', x) &= p_c cf_s(k, x) \\
&+ q_t \left[ p_t [ -p^a(k, k_t') ] (k, k') + \beta E_t \Phi^V(k_t', x)c_{t+1}^{V} \right] \\
&+ (1 - q_t) \left[ \beta E_t \Phi^W((1 - \delta)k/\gamma, k_t'^*, - (1 - \delta)/\gamma (1 - (1 - \delta)/\gamma) k_t, x)c_{t+1}^{W} \right] \\
cf_s(k_t, x_t) &= (1 - \nu) (\nu/\omega) \uparrow/(\nu - 1) (z_t \omega_t)^{1/(\nu - 1)} k_t^\nu/(\nu - 1) \\
\omega_t &= \psi/\omega_t \\
q_t &= m_t (\phi/(1 - \phi))^{\gamma - 1} \\
\Phi^W(k, k_t'^*) c_{t+1}^{W} &= E_x W_t(k, x') \\
ac_t &= q_t p_t \frac{\omega_t}{\omega_t} + (1 - q_t) \beta E_t ac_{t+1} \\
q_t p_t p^a(k, k_t'^*) \gamma &= q_t \beta E_t \Phi^V(k_t'^*, x)c_{t+1}^{V} + (1 - q_t) \beta E_t \Phi^W((1 - \delta)k_t/\gamma, k_t'^*, x)c_{t+1}^{W} \\
I_t &= \sum_{i, j} \mu_t^V(k_t, x_j)(\nu/\omega_t) \uparrow/(\nu - 1) (z_t x_j)^{1/(\nu - 1)} k_t^\nu/(\nu - 1) \\
&+ \sum_{i, j} \mu_t^W(k_t, x_j) q_t \gamma k_t^\nu - (1 - \delta) k_t \\
\mu_{t+1}^V(k_t', x_j') &= \sum_{i, j} \pi_s(x_j' | x_j) \mu_t^V(k_t, x_j) [\omega_t^{V, V, A}(i, i', j) + \omega_t^{V, V, NA}(i, i', j)] \\
&+ \sum_{i, j} \pi_s(x_j' | x_j) q_t \gamma k_t^\nu - (1 - \delta) k_t \\
\mu_{t+1}^W(k_t', k_t'^*, x_j') &= \sum_{i, j} \pi_s(x_j' | x_j) \mu_t^W(k_t, k_t'^*, x_j) [\omega_t^{W, V, A}(i, i', j) + \omega_t^{W, V, NA}(i, i', j)] \\
&+ \sum_{i, j} \pi_s(x_j' | x_j) q_t \gamma k_t^\nu - (1 - \delta) k_t \\
\log(m_{t+1}) &= (1 - p_m) \log(\mu^m) + p_m \log(m_t) \\
\log(z_{t+1}) &= p^* \log(z_t)
\end{align}
With the following auxiliary equations for the law of motion of the distribution:

\[
\omega_{t}^{V,A}(i,i',j) = \begin{cases} 
G(\hat{\xi}(k_i, x_i))q_t k_i^{-k_i^*(x_i)} & \text{if } k_i^*(x_i) \in [k_{i'}^{-1}, k_{i'}] \\
G(\hat{\xi}(k_i, x_i))q_t k_i^{-k_i^*(x_i)} & \text{if } k_i^*(x_i) \in [k_{i'}, k_{i'}+1] \\
0 & \text{else}
\end{cases}
\]

\[
\omega_{t}^{V,N\Delta}(i,i',j) = \begin{cases} 
G(\hat{\xi}(k_i, x_i))(1 - q_t k_i^{-k_i^*(x_i)}) & \text{if } k_i^*(x_i) \in [k_{i'}^{-1}, k_{i'}] \\
G(\hat{\xi}(k_i, x_i))(1 - q_t k_i^{-k_i^*(x_i)}) & \text{if } k_i^*(x_i) \in [k_{i'}, k_{i'}+1] \\
0 & \text{else}
\end{cases}
\]

\[
\omega_{t}^{W}(i,i',j) = \begin{cases} 
q_t k_i^{-k_i^*(x_i)} & \text{if } i_2 \in [k_{i'}^{-1}, k_{i'}] \\
dk_i^{-k_i^*(x_i)} & \text{if } i_2 \in [k_{i'}, k_{i'}+1] \\
0 & \text{else}
\end{cases}
\]

\[
\omega_{t}^{W,W}(i,i',j) = \begin{cases} 
(1 - q_t) k_i^{-k_i^*(x_i)} & \text{if } (1 - \delta)k_i / \gamma \in [k_{i'}^{-1}, k_{i'}] \text{ and } i_2 = i_2 \\
(1 - q_t) k_i^{-k_i^*(x_i)} & \text{if } (1 - \delta)k_i / \gamma \in [k_{i'}, k_{i'}+1] \text{ and } i_2 = i_2 \\
0 & \text{else}
\end{cases}
\]

Labeled equations (A.1)–(A.9) are the main equations, and all other unlabeled equations are auxiliary in defining the model equilibrium. Given \(n_x\) collocation nodes and \(n_x\) discrete grid points of \(x\), equations (A.1)–(A.9) are \(n_f = 2n_x^2n_x + 3n_x + 4\). I organize these equations in

\[(A.10) \quad \mathbb{E}_t[f(x_t, x_{t+1}, y_t, y_{t+1})] = 0,\]

where \(e_t = (e_t^y, e_t^p) \in \mathbb{R}^2\) denotes the vector of aggregate shocks, \(x_t\) denotes predetermined state variables and \(y_t\) denotes non-predetermined state variables

\[(A.11) \quad x_t = [\mu_t; \log(m_t); \log(z_t)] \in \mathbb{R}^{n_p = n_y^2n_x + n_kn_x + 2},\]

\[(A.12) \quad y_t = [e_t^V; e_t^W; \log(ac_t); \log(k^*_t); \log(p_t)] \in \mathbb{R}^{n_y = n_x^2 + 2n_kn_x + 2}.\]
The non-stochastic steady state is defined as \( f(\bar{x}, \bar{y}) = 0 \). In the general case, the model solution is given by

\[
\begin{align*}
\mathbf{y}_t &= g(\mathbf{x}_t, \zeta), \\
\mathbf{x}_{t+1} &= h(\mathbf{x}_t, \zeta) + \zeta \tilde{\sigma} \epsilon_{t+1},
\end{align*}
\]

where \( \zeta \) is the perturbation parameter and \( g : \mathbb{R}^{n_x} \times \mathbb{R}^+ \to \mathbb{R}^{n_y} \) and \( f : \mathbb{R}^{n_x} \times \mathbb{R}^+ \to \mathbb{R}^{n_x} \). The exogenous shocks are collected in \( \epsilon_{t+1} \in \mathbb{R}^{n_\epsilon} \), and \( \tilde{\sigma} \in \mathbb{R}^{n_x \times n_\epsilon} \) attributes shocks to the right equations while also scaling them (by \( \sigma^m, \sigma^z \)). To solve the two policy functions, I use a first-order approximation. I follow the perturbation algorithm in Schmitt-Grohe and Uribe (2004). This requires to compute the Jacobians of function \( f \) locally at steady state. Importantly, the algorithm in Schmitt-Grohe and Uribe (2004) checks for existence and uniqueness of a model solution.

\section*{A.3. Krusell-Smith algorithm}

This subsection shows how the model can alternatively be solved using the Krusell-Smith algorithm.

Following Krusell et al. (1998), and the adaptation for heterogeneous firms by Khan and Thomas (2008), I assume agents in my model only observe a finite set of moments, informative about the entire distribution, instead of observing \( \mu \) directly. The agents approximate equilibrium prices and the evolution of the observed moments by a log-linear rule.

I approximate the distribution \( \mu \) by the aggregate capital stock,

\[
K_t = \int_S k d\mu,
\]

and the stock of investments outstanding from the preceding period

\[
I_t^o = \int_{S^W} (\gamma k^o - (1 - \delta)k) d\mu^W.
\]

If time-to-build dropped to zero \( q = 1 \), \( I_t^o \) would constitute the investments activated in addition to new orders. I suggest the following log-linear forecast rules

\[
\begin{align*}
\log K_{t+1} &= \beta_0^K(z_t, m_t) + \beta_1^K(z_t, m_t) \log K_t + \beta_2^K(z_t, m_t) \log I_t^o, \\
\log I_{t+1}^o &= \beta_0^I(z_t, m_t) + \beta_1^I(z_t, m_t) \log K_t + \beta_2^I(z_t, m_t) \log I_t^o,
\end{align*}
\]

and the log-linear pricing rule

\[
\log p_t = \beta_0^p(z_t, m_t) + \beta_1^p(z_t, m_t) \log K_t + \beta_2^p(z_t, m_t) \log I_t^o.
\]

The forecasting and pricing rules are described by coefficients that depend on the exogenous aggregate shock. For discretized processes of \( z \) and \( m \), the equilibrium under bounded rationality with the above rules becomes computable. I use these rules to solve for the optimal policy functions and then simulate the economy and compute equilibrium prices \( p_t \) in every period \( t \). The simulated economy allows price series are then used to update the coefficients of the log-linear rules. I stop the procedure when the coefficients have converged.
Figure 7: Responses of investment orders to an adverse match efficiency shock

Notes: The impulse response functions are based on a decrease in match efficiency by one (unconditional) standard deviations starting from steady state and using the baseline calibration. Inaction measures the share of firms without outstanding orders that do not make a new order in a given period. The order backlog is the total of investments outstanding for delivery.
Figure 8: Responses under alternative fixed adjustment costs:

\[ f^E(\xi, s) = \frac{\xi w(s)}{\varphi \bar{q}} \text{ with } q(s) = \bar{q} \text{ in steady state} \]

Notes: The impulse response functions are based on a decrease in match efficiency by one (unconditional) standard deviations starting from steady state and using the baseline calibration. ‘Direct effect’ are the impulse responses when aggregate TFP changes are eliminated through opposing aggregate productivity (z) shocks. Aggregate TFP is computed as \( TFP = \log(Y_t) - \alpha \log(K_t) - \nu \log(L_t) \).
Figure 9: Cumulative impulse responses under baseline identification scheme

Notes: Solid, blue lines show (selected) responses to a match efficiency shock, under the baseline identification scheme. Shaded, gray areas illustrate the associated 90% confidence intervals.
Figure 10: Cumulative impulse responses under robustness identification scheme

Notes: Solid, blue lines show (selected) responses to a match efficiency shock under the baseline identification scheme. Dotted, blue lines show the identified set under bounds on the elasticities, see Table III. Shaded, gray areas illustrate the 90% confidence intervals for the identified sets.
C.2. Relation of match efficiency shock with conventional shocks

TABLE IV
Correlogram of match efficiency shocks with various shocks (in %)

<table>
<thead>
<tr>
<th>lags/forwards (in quarters)</th>
<th>-4</th>
<th>-3</th>
<th>-2</th>
<th>-1</th>
<th>0</th>
<th>+1</th>
<th>+2</th>
<th>+3</th>
<th>+4</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFP</td>
<td>-7</td>
<td>-5</td>
<td>0</td>
<td>0</td>
<td>-3</td>
<td>-1</td>
<td>-3</td>
<td>-7</td>
<td>-8</td>
</tr>
<tr>
<td>TFP: util</td>
<td>-9</td>
<td>-13*</td>
<td>4</td>
<td>7</td>
<td>-5</td>
<td>-6</td>
<td>-4</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>TFP: I, util</td>
<td>-3</td>
<td>-15**</td>
<td>2</td>
<td>11</td>
<td>3</td>
<td>-3</td>
<td>3</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>TFP: C, util</td>
<td>-10</td>
<td>-8</td>
<td>4</td>
<td>3</td>
<td>-9</td>
<td>-7</td>
<td>-7</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>MP: RR</td>
<td>2</td>
<td>8</td>
<td>4</td>
<td>2</td>
<td>-1</td>
<td>6</td>
<td>4</td>
<td>9</td>
<td>11</td>
</tr>
<tr>
<td>Oil</td>
<td>-1</td>
<td>0</td>
<td>-2</td>
<td>-2</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>9</td>
<td>-4</td>
</tr>
<tr>
<td>Defense</td>
<td>-12</td>
<td>-15**</td>
<td>-2</td>
<td>-3</td>
<td>-16**</td>
<td>-4</td>
<td>-8</td>
<td>-1</td>
<td>-10</td>
</tr>
<tr>
<td>Tax</td>
<td>2</td>
<td>-6</td>
<td>2</td>
<td>4</td>
<td>1</td>
<td>-13</td>
<td>9</td>
<td>4</td>
<td>-2</td>
</tr>
</tbody>
</table>

Note: The table shows the correlation of match efficiency shocks (backlog ratio ordered first) with various shocks at lags/forwards between -4 and +4 quarters. */**/*** denote 10%/5%/1% significance levels, respectively.

The first four shocks series are constructed in Fernald (2014) and describe total factor productivity (TFP), utilization-adjusted TFP (TFP: util), utilization-adjusted TFP in producing equipment and consumer durables (TFP: I, util), and utilization-adjusted TFP in producing non-durable consumption goods (TFP: C, util). (MP: RR) refers to the monetary policy shocks based on the narrative approach developed in Romer and Romer (2004) and extended by Coibion (2012). The oil price shocks (Oil) are based on Ramey and Vine (2010), who account for (occasional) price controls and entitlement systems. The last two variables are fiscal shocks as surprise defense expenditures (defense) as proposed by Ramey and Shapiro (1998), and tax shocks sourced from Mertens and Ravn (2011), who employ a narrative approach to identify tax liability shocks based on Romer and Romer (2010).