Wage Setting and Passthrough: The Role of Market Power, Production Technology and Adjustment Costs*

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Abstract

How much do adjustment costs, labor market power and production complementarities matter for wage setting and passthrough? We develop a general theoretical framework and empirical identification strategy illustrating how firm productivity impacts wages in imperfect labor markets. We estimate firm-level distributions of productivity, worker ability, markdowns, passthrough and labor-supply elasticities using Danish data. Typical firms respond to 1% productivity increases by lowering markdowns 1.7% and increasing marginal productivity 2.1% — increasing wages by 0.4%. Adjustment costs induce firms to hoard workers and increase markdowns in response to negative shocks. Labor market power and adjustment costs reduce passthrough, decreasing wage volatility by 77%.

JEL Codes: E2, J2, D24, J42

Keywords: TFP, Productivity, Passthrough, Wage Setting, Imperfect Competition, Markdowns, Market Power, Monopsony, Adjustment Costs, Income Risk.

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1 Introduction

How much do workers' wages change when firms become more (or less) productive? Do firms pass productivity shocks to wages mainly through the impact on their marginal revenue product of labor (MRPL) or through the firm's ability to mark wages down below marginal productivity? How do market power and adjustment costs affect this passthrough and, ultimately, workers' income volatility?

To answer these questions, we develop a general dynamic structural model of firms and wage setting in imperfect labor markets. Our model nests three key mechanisms that generate a link between shocks to firms' total factor productivity (TFP) and workers' wages: labor market power, production technology, and labor adjustment costs. Critically, we show that the wedge (markdown) between the firm's wage and the MRPL depends not just on the labor supply elasticity faced by the firm, but also on the curvature of labor demand, the marginal non-wage (adjustment) costs of labor, and the expected marginal future value of labor. We use the model to build intuition about how firm shocks affect wage and employment dynamics through these three mechanisms.

We estimate our model and recover the joint distribution of firm productivity, worker ability, production output elasticities, ability-adjusted wages, and markdowns. Using the estimated model, we obtain the distribution of passthrough elasticities across firms, where we define "passthrough" as the total elasticity of (ability-adjusted) hourly wages with respect to firm idiosyncratic TFP. We decompose these passthrough elasticities into the effect of TFP shocks on the MRPL and on the markdown. Our framework also allows us to estimate the distribution of firm-level labor supply elasticities separately from markdowns, which helps us to disentangle the determinants of wage markdowns and to quantify the effects of labor adjustment costs on wages and passthrough. Finally, we investigate and quantify how each of the mechanisms—production technology, market power, and adjustment costs—play a role in wage setting and passthrough.

A large literature considers how wage setting and market power relate to productivity, but often makes strong assumptions on the nature of production and the structure of labor markets. These assumptions, such as using log-linear or value-added production functions, or an absence of adjustment frictions, have strong implications for empirical findings and theoretical interpretation. In this paper, we provide a more general framework which relaxes some of these key assumptions. Importantly, our approach achieves identification of the model and empirical distributions of interest without imposing shape or functional-form assumptions on the nature of production, labor supply, and labor adjustment costs. We contribute to the literature in three additional ways. First, we provide intuition for and the magnitudes of the biases which result from these assumptions on production and labor markets. Second, we resolve a puzzle in the literature about why many workers are paid more than their marginal product. Third, we theoretically and quantitatively decompose the channels linking firm productivity to wages, providing new results on how productivity drives market power, input demand, and wage volatility.

We estimate the model using a rich administrative data set from Denmark, which includes detailed demographic information on the population of workers matched to financial and production data for the universe of private sector firms. Our estimation procedure builds on the non-parametric methods proposed by Gandhi, Navarro and Rivers (2020)—hereafter GNR—which we enhance by incorporating dynamic labor inputs, imperfect competition in the labor market, and labor adjustment costs, therefore allowing contemporaneous productivity shocks to affect labor input decisions and wages in current and future periods. Using data on hourly wages, worker characteristics and firm characteristics, we separately identify unobserved worker ability from (potentially correlated) firm productivity for every worker and firm in our sample. The result is the joint distribution of worker ability, ability-adjusted hourly wages, firm productivity, output elasticities, and markdowns.

Our estimated model produces novel results relative to the literature. First, we find that while the mean firm pays workers 83% of their marginal product, a significant fraction of firms pay their workers more than their marginal product.[1] Although perhaps puzzling, this finding is consistent with our model and, in particular, with an important role for adjustment costs and firm dynamics in wage setting. Second, we find an average labor supply elasticity of 2.7, which implies that the mean firm would pay workers only 73% of their marginal product absent adjustment costs.[2] This difference indicates that firms are generally constrained by adjustment costs and thus hoard workers relative to the unconstrained level of employment. While market power allows firms to pay workers less

[1]Other recent studies (e.g., Brooks *et al.* (2021) and Yeh *et al.* (2022)) also find that a significant fraction of firms have markdowns greater than one. .

[2]Our method allows us to separately identify the distributions of firm-level labor supply elasticities and markdowns. This is different from the standard approach of estimating one in order to obtain the other, which necessarily precludes adjustment costs and firm dynamics. See Yeh *et al.* (2022), Lamadon *et al.* (2022), Berger *et al.* (2022) and Azar *et al.* (2022) for recent examples.

than their marginal product, the presence of adjustment costs increases average wages relative to a setting without such frictions. Third, returns to scale increase with firm size, and output is much more sensitive to changes in intermediate inputs than labor or capital. This implies that the MRPL (and thus markdowns) are more responsive than wages to productivity shocks. Fourth, we find that markdowns are decreasing in worker ability, which suggests that an average reduction in firms' labor market power (an increase in markdowns) would disproportionately benefit high skill workers.[3]

We then use the model to recover the elasticity of firm-level wages with respect to changes in total TFP, and to persistent and transitory TFP shocks. We find an average passthrough elasticity of 0.40 indicating that a one standard-deviation change in TFP results in a 6% change in annual salary for a worker at an average firm in Denmark.[4] This passthrough is asymmetric (larger for positive shocks), long-lasting, and driven by idiosyncratic rather than aggregate or industry-level risk. We show that passthrough from productivity to the MRPL is much greater than one—a 1% persistent increase in TFP results in a 2.1% increase in MRPL—due to the complementarity of intermediate inputs and labor in production, and to the flexibility of the intermediate input relative to labor (which is subject to adjustment costs). At the same time, that same TFP shock leads to a 1.7% decrease in markdowns (the share of the MRPL paid in wages), indicating that firms have significant flexibility in setting wages below the marginal product of labor. Notably, aggregate shocks are fully passed to wages (an elasticity close to one) through the MRPL and have no effect on markdowns, consistent with inelastic short-run aggregate labor and material supply curves.

We find significant heterogeneity in passthrough across firms, driven by differences in production technology, market power, and labor adjustment costs. In particular, passthrough declines with firm productivity, firm size, and labor market share, which is consistent with market power as a driver of wage passthrough. The passthrough elasticity also declines with measures of adjustment costs, and firms are very responsive to small positive productivity shocks, but do not adjust wages in response to small negative shocks. Firm-level differences in the output elasticities of labor and materials are significantly related to passthrough, with the materials channel dominating.

[3] We broadly define the markdown as $\mu \equiv Wage/MRPL$, so a decrease in the markdown is a decrease in the share of the MRPL paid to workers in wages. We use this language throughout the paper.

[4] We find that larger firms tend to have much lower passthrough elasticities, implying that the average worker's passthrough elasticity will be somewhat smaller. See Chan *et al.* (2022) for an analysis of worker-level wage passthrough using the same data.

To quantify the importance of the aforementioned mechanisms, we perform a series of exercises where we turn off one or two of the mechanisms in our structural model and re-estimate the counter-factual passthrough elasticity distribution. We find that labor market frictions such as labor market power and adjustment costs both play an crucial role in generating the passthrough elasticity that we observe in the data. In fact, removing all labor market imperfections other than a simple fixed markdown (as in a model with atomistic firms and log-linear labor supply) increases average passthrough from 0.38 to 2.22. This indicates that the presence of market imperfections significantly reduces passthrough and thus labor income risk, thereby mitigating the exposure of workers to firm risk. In fact, the wage volatility arising from firm risk is 4 times higher in a setting without frictions than in our baseline results–implying that labor market imperfections reduce this wage volatility by over 77%.

Related Literature. Our paper builds on several literatures looking at the link between firm dynamics, wage setting, and productivity. Guiso *et al.* (2005), Juhn *et al.* (2018), Friedrich *et al.* (2021) and Garin and Silverio (2022) use matched employer-employee data to study the passthrough from sales or value-added shocks to worker earnings.[5] Relative to this literature, we are the first to decompose passthrough and examine how underlying productivity shocks affect hourly wages, marginal product of labor, and markdowns while estimating and controlling for unobserved worker ability. We do this through the lens of a dynamic structural model of firm behavior and wage setting which allows us to decompose and interpret the channels by which this passthrough operates. Our approach also allows us to estimate the distribution of passthrough (rent-sharing) elasticities for positive and negative shocks for the entire private sector, whereas studies using exogenous variation in outcomes such as procurement auction wins are limited to analyzing an important but small subset of firms.[6]

Our approach to estimating productivity while controlling for unobserved labor quality is similar in spirit to those proposed by Hellerstein and Neumark (2007), Fox and Smeets (2011), and more recently, Bagger *et al.* (2014) and Bagger and Lentz (2019), who

[5]There is a large and emerging literature on this topic, driven by the increasing availability of data linking measures of firm performance to worker earnings. A few examples include Cardoso and Portela (2009), Barth *et al.* (2016), Carlsson *et al.* (2015) (one of the few studies to also use structural estimates of productivity shocks), and Balke and Lamadon (2022) among others. See Card *et al.* (2018), Guiso and Pistaferri (2020) and Manning (2021) for recent surveys of the literature.

[6]For example, patent approvals (Kline *et al.*, 2019), cash windfalls from government grants (Howell and Brown, 2023), and procurement auction wins (Carvalho *et al.*, 2023).

also incorporate worker-level characteristics to control for differences in the labor quality across firms. In particular, Bagger *et al.* (2014) incorporate firm-time fixed effects into an AKM-style wage model, as we do here. We differ from their paper (and the others listed) in that we estimate productivity non-parametrically in a fully dynamic setting with adjustment costs, and we are able to separately identify transitory and persistent shocks to firms' productivity.[7]

Our characterization of how worker ability enters the firm's production function also relates to a recent literature on jointly estimating Hicks-neutral TFP and labor-augmenting technological change. Relative to other papers in this literature (e.g., Doraszelski and Jaumandreu (2018) and Demirer (2020)), we are the first to estimate time-varying firm-level measures of labor productivity in the presence of a flexible production technology, imperfect labor markets, and labor adjustment costs.

Our work also contributes to the recent literature on estimating labor market power. Other recent examples of papers estimating markdowns and labor supply elasticities include Azar *et al.* (2022), Lamadon *et al.* (2022), Yeh *et al.* (2022), Berger *et al.* (2022), and Brooks *et al.* (2021). Relative to these studies, we develop a much more flexible framework which allows the separate identification of markdowns and labor supply elasticities in the face of firm dynamics and adjustment costs in labor, controls for unobserved variation in worker quality, and permits structural counterfactuals to decompose the channels which drive markdowns and wage setting. In addition, our framework rationalizes the common finding across many such papers that some firms have markdowns greater than one.

Our approach is similar to Delabastita and Rubens (2022) who also estimate markdowns separately from labor supply elasticities and gain inference about firm collusion from the difference. Relative to their framework, we allow for heterogeneous workers, labor adjustment costs and firm dynamics in a general, non-parametric setting. Roys (2016) uses a parametric dynamic model with adjustment costs to consider the passthrough of TFP shocks to wages, but restrict their analysis to the direct and labor channels of passthrough. Instead, we quantify the importance of the materials channel and show that it can reverse the theoretical predictions of a model with only labor and/or capital inputs. Seegmiller (2021) also considers wage setting in a calibrated parametric

[7]We show this is important in the context of estimating markdowns and passthrough. Similarly, Foster *et al.* (2022) show that strong parametric assumptions about the shape of firm production functions can dramatically alter estimates of markups.

framework with wage posting, upward sloping labor supply curves and adjustment costs, finding results largely consistent with this paper.

The rest of the paper proceeds as follows. In Section 2 we derive and discuss wage setting and passthrough in a general dynamic model of labor market power and adjustment costs. In Section 3, we introduce our data sources and discuss our sample selection and in Section 4 we present our estimation strategy. Section 5 discusses our baseline model and passthrough elasticity estimates. Finally, in Section 6 we examine the degree to which the different mechanisms drive passthrough and income risk. Section 7 concludes.

2 Model of Wage Setting and Passthrough

2.1 General Model

We consider an environment with a finite number of firms indexed by j and a continuum of workers indexed by i. Firms maximize profits and operate a production function

$$Y_{jt} = F(K_{jt}, L_{jt}, M_{jt})e^{\nu_{jt}}, \tag{1}$$

which combines capital (K_{jt}), labor (L_{jt}), and intermediate inputs (M_{jt}) to produce output (Y_{jt}). The term $e^{\nu_{jt}}$ captures the firm's Hicks-neutral TFP which (in logs) follows

$$\nu_{jt} = \omega_{jt} + \epsilon_{jt} = h_j(\omega_{jt-1}) + \eta_{jt} + \epsilon_{jt}, \tag{2}$$

where ω_{jt} is the persistent component of productivity and ϵ_{jt} is an ex-post transitory shock which is observed by the firm *after* making input decisions. The persistent productivity, ω_{jt}, evolves as a firm-specific first-order Markov process with $h_j(\omega_{jt-1}) \equiv E[\omega_{jt} \mid \omega_{jt-1}]$ and innovation η_{jt}. Both η_{jt} and ϵ_{jt} are i.i.d. with mean zero.

We assume that the firm's labor input is given by an ability-weighted sum of total working hours employed by the firm

$$L_{jt} = \sum_{i \in j} A_{it} H_{ijt}, \tag{3}$$

where A_{it} represents worker i's time-varying ability (which could be a function of unobserved innate ability or observed characteristics such as education or experience) and H_{ijt} represents the quantity (in hours) of labor that individual i provides to firm j in period t.[8] This assumption means that workers are perfect substitutes in production *conditional on their ability*, A_{it}, and that firms will pay a single firm-level ability price, W_{jt}, per hour of ability-adjusted labor supplied to the firm.[9] Worker i's hourly wage is then $W_{ijt} = A_{it}W_{jt}$. We assume that the firm-level wage takes the following form: $W_{jt} = W_{jt}^c f^c(\epsilon_{jt})$, where W_{jt}^c is a contract wage rate offered by the firm when making hiring decisions and f^c is a function which represents the degree to which firms modify the ex-post wage relative to the expected wage once ϵ_{jt} is realized (e.g., performance bonuses). The expected wage then takes the form

$$\overline{W}_{jt} = E_{\epsilon_{jt}}[W_{jt}|W_{jt}^c] = W_{jt}^c \mathcal{E}^c,$$

where $\mathcal{E}^c \equiv E_{\epsilon_{jt}}[f^c(\epsilon_{jt})]$ is the expected ex-post wage adjustment. Though the value of ϵ_{jt} is unknown at the time of hiring, workers and firms know the distribution of ϵ_{jt} and the shape of $f^c(\epsilon_{jt})$, and base their employment/hiring decisions on $\overline{W}_{jt}$.

Firms differ in a set of exogenous characteristics, denoted $\overline{Z}_{jt}$, and endogenous labor force characteristics, denoted $\tilde{Z}_{jt}$. Labor markets are allowed to be imperfect, with firms facing an upward sloping labor supply curve, $L_{jt} = g\left(\overline{W}_{jt}, \overline{Z}_{jt}\right)$, which depends on the expected wage offered to workers at firm j in period t, $\overline{W}_{jt}$, and on exogenous firm characteristics, $\overline{Z}_{jt}$.[10]

We also assume that firms face a labor cost function, $\Phi_{jt} = \Phi(L_{jt}, L_{jt-1}, \overline{Z}_{jt}, \tilde{Z}_{jt}, \tilde{Z}_{jt-1})$, which could include adjustment costs in L_{jt} and $\tilde{Z}_{jt}$, the cost of providing non-pecuniary amenities to workers (which may depend on average worker age or education), or management/congestion costs (which may depend on the number or type of employees rather than just ability-adjusted hours).[11]

[8]We can rewrite the labor input as $L_{jt} = H_{jt}\bar{A}_{jt}$ where H_{jt} is the total hours of labor employed, and $\bar{A}_{jt}$ is the hours-weighted time-varying mean worker ability at the firm. This is similar to the literature which estimates firm-level labor augmenting productivity (e.g., Demirer (2020) and Doraszelski and Jaumandreu (2018)). The key difference is that those papers assume labor markets are perfectly competitive with no adjustment costs, while we achieve identification in the presence of both labor market power and dynamic adjustment costs.

[9]Firms are indifferent in production between one hour of labor from a highly skilled worker and two hours of labor from workers with half the skill of the first. The distribution of ability and number of workers within the firm may matter for the wage, however, via its effect on the labor cost function.

[10]We remain agnostic about the sources and nature of labor market imperfectness for now. This general labor supply function nests many common theoretical frameworks from the literature. We discuss several such frameworks in the next subsection.

[11]We assume the set of endogenous characteristics $\tilde{Z}_{jt}$ is not directly production relevant, but may affect the firm's decisions and behavior via the labor cost function.

We make several standard timing assumptions (see GNR for details). First, capital K_{jt} is predetermined by the investment decisions in period $t-1$. Second, firms make input and investment decisions conditional on the persistent shock η_{jt}, which they observe at the beginning of period t. Third, intermediate inputs M_{jt} are fully flexible and can be adjusted freely in response to changes in η_{jt}.[12] Finally, firms observe the transitory shock ϵ_{jt} after making input decisions, and so period-t input choices are not conditional on ϵ_{jt}.[13] Workers realized wages, however, may depend on the transitory shock. This means that the firm makes its employment decisions based on its information set in t and its expectations over the transitory shock and (therefore) the wage rate. We specify the firm's information set at the beginning of period t as $\mathcal{I}_{jt} = \left\{ \eta_{jt}, K_{jt}, L_{jt-1}, \tilde{Z}_{jt-1}, \overline{Z}_{jt}, P_t, \mathcal{I}_{jt-1} \right\}$, where $P_t = \{P_t^Y, P_t^M, P_t^I\}$ is the vector of output, materials, and investment prices which we assume the firm takes as given.

Conditional on $\mathcal{I}_{jt}$, firms maximize their present discounted stream of current and future profits by choosing their capital investment K_{jt}^I, labor input L_{jt}, materials M_{jt}, and endogenous labor force characteristics $\tilde{Z}_{jt}$. Firms thus face the following dynamic profit maximization problem:

$$\begin{aligned} V_{jt}(\mathcal{I}_{jt}) = \max_{L_{jt}, K_{jt}^I, M_{jt}, \tilde{Z}_{jt}} & E_{\epsilon_{jt}} \left[P_t^Y F(K_{jt}, L_{jt}, M_{jt}) e^{\nu_{jt}} \mid \mathcal{I}_{jt} \right] - E_{\epsilon_{jt}} \left[W_{jt} \mid W_{jt}^c \right] L_{jt} - \Phi_{jt} \\ & - P_t^I K_{jt}^I - P_t^M M_{jt} + \beta E_{\epsilon_{jt}, \eta_{jt+1}, P_{t+1}} \left[V_{jt+1}(\mathcal{I}_{jt+1}) | \mathcal{I}_{jt} \right] \end{aligned} \tag{4}$$

$$\begin{aligned} \text{s.t. } K_{jt+1} &= (1-\delta) K_{jt} + K_{jt}^I \\ L_{jt} &= L_j(\overline{W}_{jt}, \overline{Z}_{jt}) \\ \Phi_{jt} &= \Phi(L_{jt}, L_{jt-1}, \overline{Z}_{jt}, \tilde{Z}_{jt}, \tilde{Z}_{jt-1}). \end{aligned}$$

Solving the first order conditions (FOC) with respect to materials and labor gives one of the key estimating equations,

$$P_t^Y \frac{\partial F}{\partial M_{jt}} e^{\omega_{jt}} \mathcal{E} = P_t^M, \tag{5}$$

[12] Throughout the paper we refer to the flexible input M_{jt} interchangeably as either "intermediate inputs" or "materials".

[13] ϵ_{jt} therefore captures variation in output which is completely uncorrelated with inputs.

and an expression for the optimal wage paid by the firm,

$$W_{jt}=\frac{\varepsilon^{L}_{\overline{W}jt}}{1+\varepsilon^{L}_{\overline{W}jt}}\left(\overline{MRPL}_{jt}-\frac{\partial\Phi_{jt}}{\partial L_{jt}}+\frac{\partial\overline{V}_{jt+1}}{\partial L_{jt}}\right)\frac{f^{c}(\epsilon_{jt})}{\mathcal{E}^{c}}, \tag{6}$$

where $\varepsilon^{L}_{\overline{W}_{jt}}$ denotes the elasticity of the labor supply curve with respect to the expected wage.[14] $\overline{MRPL}_{jt}$ and $\overline{V}_{jt+1}$ denote the expected values of the $MRPL_{jt}$ and (discounted) value function V_{jt+1} respectively. Finally, wage equation can be written as $W_{jt}=\mu_{jt}MRPL_{jt}$ which defines the markdown μ_{jt} as the multiplicative wedge between the wage level and MRPL. The markdown, μ_{jt}, is then

$$\mu_{jt}=\frac{\varepsilon^{L}_{\overline{W}jt}}{1+\varepsilon^{L}_{\overline{W}jt}}\left(1-\left(\frac{\partial\Phi_{jt}}{\partial L_{jt}}-\frac{\partial\overline{V}_{jt+1}}{\partial L_{jt}}\right)\overline{MRPL}_{jt}^{-1}\right)\frac{f^{c}(\epsilon_{jt})}{\mathcal{E}^{c}}\frac{\mathcal{E}}{e^{\epsilon_{jt}}}, \tag{7}$$

where we denote the constant $\mathcal{E}\equiv E\left[e^{\epsilon_{jt}}\right]$.[15]

Unlike in static monopsony and oligopsony models (e.g., Berger *et al.* (2022) and Lamadon *et al.* (2022)), where markdowns only depend on the labor supply elasticity, here the markdown also depends on the marginal non-wage cost of labor $(\partial\Phi_{jt}/\partial L_{jt})$, the expected marginal future benefit of labor, $\left(\partial\overline{V}_{jt+1}/\partial L_{jt}\right)$, the expected MRPL, and the ex-post wage adjustment function. In Section 4, we show how to recover the distribution of productivities, ability-adjusted firm wages, markdowns and marginal revenue products without requiring any knowledge of the labor supply curve or labor cost functions.

2.2 Decomposing Passthrough

Our notion of passthrough is the *elasticity* of wages with respect to productivity, i.e., the *total* derivative of log wages with respect to log TFP, denoted ε^{W}_{TFP}. Though we are primarily interested in the passthrough of persistent shocks to productivity, ε^{W}_{η}, we also consider passthrough from the transitory shock, $\varepsilon^{W}_{\epsilon}$.[16] The log wage is the sum of

[14] We assume that $\overline{Z}_{jt}$ is exogenous and deterministic. Similarly P_t are exogenous and follow a known process. We derive all the first order conditions in Appendix B.1.

[15] Note that $\overline{MRPL}_{jt}=MRPL_{jt}\frac{\mathcal{E}}{e^{\epsilon_{jt}}}$

[16] We focus on the persistent TFP shock passthrough because the passthrough from persistent shocks to TFP to wages, MRPL, and markdowns reflect firms' decisions and input choices whereas the passthrough from transitory shocks to wages does not. We discuss the passthrough from transitory shocks later in this section. Note that passthrough of η_{jt} to the expected wage and MRPL is equal to passthrough from η_{jt} to realized wages and MRPL.

the firm's (log) MRPL and (log) markdown, $w_{jt} = mrpl_{jt} + \log \mu_{jt}$.[17] Therefore, the passthrough to wages could arise from changes in the MRPL, changes in the markdown, or both. To examine each channel, we decompose the wage passthrough elasticity into the passthrough elasticity for each of these components, that is

$$\varepsilon^W_{\eta_{jt}} = \frac{\mathrm{d}mrpl_{jt}}{\mathrm{d}\eta_{jt}} + \frac{\mathrm{d}\log \mu_{jt}}{\mathrm{d}\eta_{jt}}.$$

Using the log of the firm's MRPL, $mrpl_{jt} = \log P^Y_t + \log(\frac{\partial}{\partial L_{jt}} F(K_{jt}, L_{jt}, M_{jt})) + \nu_{jt}$, we get the following expression for the passthrough from η_{jt} to the MRPL:

$$\frac{\mathrm{d}mrpl_{jt}}{\mathrm{d}\eta_{jt}} = \underbrace{\frac{\partial f^L_{jt}}{\partial k_{jt}} \frac{\mathrm{d}k_{jt}}{\mathrm{d}\eta_{jt}}}_{\text{Capital channel}} + \underbrace{\frac{\partial f^L_{jt}}{\partial l_{jt}} \frac{\mathrm{d}l_{jt}}{\mathrm{d}\eta_{jt}}}_{\text{Labor channel}} + \underbrace{\frac{\partial f^L_{jt}}{\partial m_{jt}} \frac{\mathrm{d}m_{jt}}{\mathrm{d}\eta_{jt}}}_{\text{Material channel}} + \underbrace{1}_{\text{Direct Channel}}, \tag{8}$$

where $f^L_{jt} \equiv \log(\partial F(K_{jt}, L_{jt}, M_{jt})/\partial L_{jt})$. Passthrough to the MRPL operates through four channels. The capital channel is zero since capital is pre-determined. The labor channel will be negative if F is concave in L_{jt} since the MRPL is decreasing in L_{jt}. The material channel will be positive if the MRPL is increasing in material (i.e., if labor and materials are complements in production). Finally, the direct channel equals one since η_{jt} enters ν_{jt} linearly. Whether passthrough to the MRPL is greater or less than one depends on the relative magnitudes of the labor and material input channels, which in turn depend on the input demand elasticities ($dl_{jt}/d\eta_{jt}$ and $dm_{jt}/d\eta_{jt}$) and the shape of the production function. Note that if the material channel was absent (as in models with value-added production functions), we would conclude that passthrough to the MRPL must be less than one.

Similarly, taking the total derivative of equation 7 with respect to η_{jt}, we can write the passthrough elasticity of η_{jt} to markdowns as

$$\frac{\mathrm{d}\log \mu_{jt}}{\mathrm{d}\eta_{jt}} = \underbrace{\frac{\mathrm{d}}{\mathrm{d}\eta_{jt}} \log \frac{\varepsilon^L_{Wjt}}{1 + \varepsilon^L_{Wjt}}}_{\frac{\mathrm{d}\log \mu^\varepsilon_{jt}}{\mathrm{d}\eta_{jt}}} + \underbrace{\frac{\mathrm{d}}{\mathrm{d}\eta_{jt}} \log \left(1 - \left(\frac{\partial \Phi_{jt}}{\partial L_{jt}} - \frac{\partial \overline{V}_{jt+1}}{\partial L_{jt}}\right) \overline{MRPL}^{-1}_{jt}\right)}_{\frac{\mathrm{d}\log \mu^\Phi_{jt}}{\mathrm{d}\eta_{jt}}}. \tag{9}$$

The first term ($\mathrm{d}\log \mu^\varepsilon_{jt}/\mathrm{d}\eta_{jt}$) shows that passthrough to markdowns depends on the labor

[17] Throughout this paper, we use capital letters to denote variables in levels and lowercase letters to denote variables in logs unless otherwise specified.

supply elasticity. The second term ($\mathrm{d}\log\mu^{\Phi}_{jt}/\mathrm{d}\eta_{jt}$) shows that passthrough to markdowns also depends on firms' adjustment costs, the continuation value of the firm, and the *expected* marginal productivity of labor. Notice that passthrough to the markdown will generally be negative under standard assumptions. First, if the labor supply elasticity decreases as firms move up their labor supply curve (as in Berger *et al.* (2022)), then the first term will be negative, as a productivity shock increases employment (and labor market share), thus decreasing the supply elasticity. Secondly, if adjustment costs are convex in labor inputs, an increase in productivity will increase marginal labor costs. In the case that the change in net marginal costs $\left(\partial\Phi_{jt}/\partial L_{jt} - \partial\overline{V}_{jt+1}/\partial L_{jt}\right)$ outweighs the change in the expected marginal benefit $\left(\overline{MRPL}_{jt}\right)$, this second term will also be negative. We test these predictions in sections 5 and 6.

To gain intuition on how each mechanism drives passthrough and wage setting, we consider a simplified version of our model without these mechanisms, where the labor supply elasticity is a constant, there are no adjustment costs, and the production function is Cobb-Douglas.[18] In this simple setting with $\varepsilon^L_W < \infty$ (similar to Lamadon *et al.* (2022), Kroft *et al.* (2020), and Card *et al.* (2018)) passthrough to wages is a constant common to all firms and passthrough to markdowns is zero. This constant is increasing in output elasticities and decreasing in the labor supply elasticity, ε^L_W. We then consider three variations where we separately add each mechanism. If we add our flexible production technology to the simple setting, passthrough to markdowns will still be zero, but passthrough to wages will be heterogeneous and increasing in firm size and productivity. If we instead allow firms to face adjustment costs, passthrough to markdowns will be heterogeneous and positively (negatively) correlated with passthrough to wages (MRPL). Finally, if we instead allow the labor supply elasticity to be endogenous, passthrough patterns depend on the nature of the (unknown) labor supply model. Under oligopolistic logit and CES models of labor supply (as in Berger *et al.* (2022) and Chan *et al.* (2021)), passthrough to wages will be decreasing in firm size and productivity, while passthrough to the MRPL and markdowns will both be increasing (in absolute value) in size.

In section 6.1 we test these model predictions empirically, and use a series of counterfactual exercises to measure the relative importance and magnitude of each of these mechanisms in the model and data. We next discuss the data we use, and our strategy for identifying the theoretical objects of interest in the data.

[18] See Appendix B.3 for derivation details and further discussion.

3 Data and Institutional Background

We use linked firm- and worker-level administrative registers provided by Statistics Denmark containing detailed panel information on firm and worker characteristics.

Worker-Level Data. We obtain worker-level information from the Integrated Database for Labor Market Research (Statistics Denmark, 2023a), which is an annual database containing employment and demographic information for the entire Danish population between 1991 and 2018. From this data set, we obtain several key variables such as annual income and hourly wages for each job held during the year, the total number of hours and days worked in each job, occupation, labor market status, position within the firm, age, gender, education, and tenure within the firm.

Firm-Level Data. We draw firm-level information from the Firm Statistics Register (Statistics Denmark, 2023b) which contains annual accounting and input use data for the universe of the Danish private sector between 1996 and 2010.[19] The key firm-level variables we use are revenue, value-added, capital stock, expenditure on intermediate inputs and materials, and employment (in full-time equivalents), as well as firm age, geographic location, and industry.

Sample Selection and Characteristics. We impose minimal sample selection criteria. To identify the worker-level distribution of ability and their contribution to each firm's labor input, we use worker level data between 1991 and 2010 covering employment, wages, and demographics. We consider workers aged 15 and above, keeping information on up to three job spells per year.[20] After also applying our firm selection criteria (below), this leaves us with 8.8 million worker-year observations. Table A.4 displays descriptive statistics of our sample of workers in terms of annual earnings, annual wages, hourly wages, and age distributions. All values are expressed in 2010 US dollars.

On the firm side, we drop observations with imputed variables, observations without price deflators (pre-1999), and observations without all the variables needed for estimating productivity (firms with missing capital, revenue, materials, labor, or our firm-level labor characteristics for year t or $t-1$). This leaves us with about 550,000 firm-level

[19]The firm register begins in 1996 with coverage of the manufacturing sector. Other sectors were added from 1997-2000, with universal coverage achieved in 2000.

[20]Discarding information on non-primary job spells when constructing firm-level labor inputs would lead to significant bias when estimating firm productivity if the degree of part-time labor varies systematically across firms.

observations. Since our passthrough regressions are in changes (requiring lags), our sample for the final estimation is about 374,000 firm-year observations.[21] Table A.5 displays cross-sectional moments for various firm characteristics including employment, revenue, value added, value added per worker and firm age.

Danish Labor Market Features. The Danish labor market is characterized by lax employment protection, with most worker wages during our sample period being set at the firm level rather than through collective bargaining.[22] This has arisen due to a labor market system dubbed "flexicurity" which combines comparatively low barriers to firing and hiring with a generous safety net for the unemployed (Andersen and Svarer, 2007). The result is a labor market with relatively high rates of turnover coupled with short unemployment spells, even during recessions (Andersen, 2021). Similarly, wage flexibility during our sample period is high compared with other countries despite the fact that unions, firms, and the government do interact to determine working conditions (and sometimes wage floors) for many industries (Dahl *et al.*, 2013).[23]

4 Empirical Strategy

In this section, we describe how we use the structure of our model to estimate the distributions of worker ability, firm-level wages and production technologies, and passthrough elasticities while making as few assumptions on the nature of production, labor market competition, and adjustment costs as possible.

4.1 Estimating Worker Ability and Firm-Level Wages

Firms in our model use a composite of ability-adjusted hours as their labor input. Hence, to construct the firm's labor input and estimate firm productivity, we need to separately identify the distributions of worker-level ability (A_{it}) and firm-level wages (W_{jt}), neither of which are directly observed in the data. Recall that workers are perfectly

[21] To avoid the disclosure of any sensitive information, we have rounded the number of observations throughout the paper to the nearest thousand.

[22] This has not always been the case in Denmark, but the state-mandated wage-setting policies which had been in place for most workers before 1990 were almost entirely dismantled during the early 1990s.

[23] Income inequality in Denmark is lower relative to other countries, but it has increased in recent years, in part, because of a significant decline in unemployment insurance (Leth-Petersen and Sæverud, 2021). Income inequality has also increased at the top of the distribution, following similar trends in other countries such as the United States. The distribution of earnings growth (a measure of income volatility) for Danish workers is also similar to those in the United States and other countries. See Leth-Petersen and Sæverud (2021) and Busch *et al.* (2022), among others.

substitutable in production conditional on their ability (by assumption), so that workers' hourly wages take the form $W_{ijt} = A_{it} \times W_{jt}$. We leverage this log additivity to estimate worker ability and firm wages jointly and assume that ability takes the form:

$$A_{it} = A_i \times \Lambda_t(X_{it}) \Longrightarrow \log A_{it} = a_i + \lambda_t(x_{it}), \tag{10}$$

where A_i denotes innate ability which is invariant over time. The component $\Lambda_t(X_{it})$ denotes the contribution to productive ability of time-varying worker characteristics (such as education or experience), where the level of contribution from each characteristic may also change over time. The worker-level log hourly wage therefore takes the form:

$$w_{ijt} = a_i + \lambda_t(x_{it}) + w_{jt}. \tag{11}$$

If we further assume that the time-varying worker characteristic function takes the form $\lambda_t(x_{it}) = \sum_k \lambda_{kt} x_{ikt}$, where k indexes worker characteristics, the individual log-wage function in equation 11 becomes $w_{ijt} = a_i + \sum_k \lambda_{kt} x_{ikt} + w_{jt}$. This wage function resembles the two-way fixed effect model introduced by Abowd *et al.* (1999) (AKM hereafter). We use a similar strategy in our estimation and identification. Specifically, we estimate the individual wage equation as

$$w_{ijt} = a_i + \sum_k \lambda_{kt} x_{ikt} + w_{jt} + \xi_{ijt}, \tag{12}$$

where ξ_{ijt} is a residual that we treat as measurement error.

Our specification differs from the standard two-way fixed effects regression model commonly used in the literature in two crucial aspects. First, we use the match-specific hourly wage as our dependent variable. This means that, unlike approaches which use annual earnings, we include full and part-time job spells in our sample without confounding variation in the wage rate received by a worker with the number of hours worked by an individual at a firm during the year.[24] This is important for the estimation of firm-level TFP: if we were to restrict our analysis to only full-time workers, or to only a worker's primary (i.e., largest earning) job, we would be under-counting the labor input for firms that use a high share of part-time workers (which may vary with firm productivity).

Second, we do not impose that the contribution of the firm to workers' wages is fixed,

[24]See Song *et al.* (2019) for a discussion on how papers using annual earnings data deal with this.

as in the standard AKM model, but rather allow it to vary over time, as indicated by the time subscript on w_{jt} in equation 12. Allowing time-varying firm effects is a necessary condition for our analysis in that we allow firms' idiosyncratic productivity shocks, or other changes in firms' characteristics, to impact workers' wages.[25]

To identify equation 12, we construct a connected set of firms using information on all of the firms in which an individual worked during a given year, along with the corresponding wages and hours. Hence, in our data set, an individual can appear in different firms within the same year working at different hourly wages. Multiple worker-year observations increase the number of firm connections, the number of individual-level observations for each worker, and the size of the connected set.[26]

We estimate the model in Equation 12 using the largest connected set of firm-time observations which includes 94% of the firms and 99% of all of the workers in our original sample.[27] In our estimation, we consider a rich set of worker-level observables including dummies for occupation, education, and position within the firm, as well as continuous measures of labor market experience and tenure within the firm, most of which are typically absent in other administrative data sets. Similarly to Card *et al.* (2013), we allow for the effect of education, occupation, and worker position within the firm to change over time in order to capture both the effects of time-varying observable individual characteristics and aggregate trends such as skill-biased technical change

[25] As we further discuss in Appendix A, to identify the parameters of Equation 12, we require that labor mobility is not correlated with the residual ξ_{ijt}. However, we do allow workers to switch firms in response to shifts in w_{jt}, thereby allowing the passthrough from firm productivity to wages to play a role in sorting and worker mobility decisions. The standard AKM model with time-invariant fixed effects assumes there is no such relationship and is thus inconsistent with our analysis. A few other papers also allow for time-varying coefficients in AKM regressions. The first example, to our knowledge, is Bagger *et al.* (2014) who allow for occupation-firm fixed and firm-time effects in their wage model. Bagger and Lentz (2019) also incorporate time-varying firm-level observables into their estimation. More recent examples include Chan *et al.* (2022), Engbom *et al.* (2023) and Lachowska *et al.* (2023) who also estimate a wage equation with time-varying firm effects. Gregory (2020) analyzes labor earnings growth in the context of a two-way fixed effect regression model, implicitly assuming a time-varying firm effect.

[26] Holding multiple jobs in a particular year is quite common among workers in our sample: 54.4% of workers have held a second job at least once during a year whereas 4.7% of workers have held three or more jobs. In our sample, we consider a worker's top three jobs in a given year (defined by total hours worked that year). It is important to note that, although using multiple firm-year observations per worker improves the accuracy of our estimates, it is not necessary for the identification of the model.

[27] In Appendix A, we provide a graphical representation of how we construct our connected set using all job observations for each worker in the sample. Importantly, if we restrict our sample to only include the firm that provides the largest labor earnings for each worker (defined by total annual earnings), the largest connected set decreases in size, covering only 89% of firms.

and outsourcing. Our estimates are in line with previous studies.[28] The estimation of equation 12 gives us two crucial distributions. First, a measure of each individual's ability $\hat{A}_{it} = \exp(\hat{a}_i + \sum_k \hat{\lambda}_{kt} x_{ikt})$ which we use to construct the firm-level labor input L_{jt}. Second, the firm's ability-adjusted hourly wage W_{jt} which we use to estimate our passthrough elasticities.

4.2 Estimating Firm Productivity

Given our estimates of worker ability, we can proceed to estimate the production function and the distribution of firm-level productivity.[29] To do this, recall the firm's FOC with respect to M_{jt} shown in equation 5:

$$P_t^Y \frac{\partial F}{\partial M_{jt}} e^{\omega_{jt}} \mathcal{E} = P_t^M.$$

Multiplying both sides of the equation by M_{jt}/Y_{jt}, taking logs, and rearranging provides us with the following equation

$$\begin{aligned} s_{jt} &= \ln \mathcal{E} + \ln D(k_{jt}, l_{jt}, m_{jt}) - \epsilon_{jt}, \\ &\equiv \ln(D^{\mathcal{E}}(k_{jt}, l_{jt}, m_{jt})) - \epsilon_{jt}, \end{aligned} \tag{13}$$

where $s_{jt} \equiv \ln(P_t^M M_{jt}/P_t^Y Y_{jt})$ is the log share of intermediate input expenditures in revenues and $D(k_{jt}, l_{jt}, m_{jt}) \equiv \frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt})$ is the output elasticity of materials.[30] Since $\mathbb{E}[\epsilon_{jt}] = 0$, and ϵ_{jt} is uncorrelated with period t firm inputs, we can estimate equation 13 non-parametrically and identify the function $D^{\mathcal{E}}$. Given $\epsilon_{jt} = \ln\left(D^{\mathcal{E}}(k_{jt}, l_{jt}, m_{jt})\right) - s_{jt}$, we can identify $\mathcal{E}$, which then gives the elasticity $D(k_{jt}, l_{jt}, m_{jt}) = D^{\mathcal{E}}(k_{jt}, l_{jt}, m_{jt})/\mathcal{E}$. Knowledge of the elasticity then allows us to estimate the full production function non-parametrically.

Note that $f(k_{jt}, l_{jt}, m_{jt}) = \int D(k_{jt}, l_{jt}, m_{jt}) dm_{jt} - \Psi(k_{jt}, l_{jt})$ for some unknown function Ψ. Then, define $\tilde{y}_{jt} \equiv y_{jt} - \epsilon_{jt} - \mathcal{D}(k_{jt}, l_{jt}, m_{jt})$ where

[28] As shown in Appendix A, our estimates are in line with other recent studies that implement the AKM estimator (see for instance, Sorkin (2018), Song *et al.* (2019), and Lamadon *et al.* (2022)). We find that around 48% of the variance of the log hourly wages is accounted for by workers' observed and unobservable characteristics, 16% is accounted for by firms' time-varying characteristics, and sorting accounts for almost none of the variation in hourly wages.

[29] Our identification strategy (and notation) for this component of the model builds on the non-parametric identification approach developed in GNR with a few modifications which we discuss in the text.

[30] Here we have assumed, as in GNR, that $F(K_{jt}, L_{jt}, M_{jt})$ can be expressed in logs as $f(k_{jt}, l_{jt}, m_{jt})$.

$\mathcal{D}(k_{jt}, l_{jt}, m_{jt}) \equiv \int D(k_{jt}, l_{jt}, m_{jt}) dm_{jt}$.[31] We then have $\tilde{y}_{jt} = -\Psi(k_{jt}, l_{jt}) + \omega_{jt}$. Using the structure of ω_{jt} from equation 2, we get another estimating equation:

$$\tilde{y}_{jt} = -\Psi(k_{jt}, l_{jt}) + h_j(\tilde{y}_{jt-1} + \Psi(k_{jt-1}, l_{jt-1})) + \eta_{jt}, \tag{14}$$

where $\tilde{y}_{jt}$ is observable given our first-stage estimates of ϵ_{jt} and $\mathcal{D}(k_{jt}, l_{jt}, m_{jt})$. We treat both Ψ and h_j non-parametrically, estimating each using complete polynomial sieve estimators following GNR.[32] While equation 13 can be estimated using non-linear least squares, equation 14 depends on l_{jt} which is endogenous and correlated with η_{jt}. The model assumptions on the firm's information set and dynamic maximization problem imply $E[\eta_{jt}|k_{jt}, l_{jt-1}, k_{jt-1}, \overline{Z}_{jt}, \tilde{Z}_{jt-1}] = 0$ which means we can use functions of the set $\{k_{jt}, l_{jt-1}, k_{jt-1}, \overline{Z}_{jt}, \tilde{Z}_{jt-1}, \tilde{y}_{jt-1}\}$ as instruments to identify equation 14. In particular, the presence of adjustment costs means we can use functions of $\tilde{Z}_{jt-1}$ to identify the contribution of l_{jt}. [33]Our setting differs from GNR, where labor is pre-determined (and thus does not require additional instruments), and differs from the settings in most of the production function based market power literature (e.g.: Yeh *et al.* (2022)) where labor is flexible with no adjustment costs (which may lead to identification issues when using lags of inputs as instruments).[34]

As is standard in the literature (Syverson, 2011), we measure Y_{jt} as real (deflated) revenues, K_{jt} as the real value of the capital stock (using the perpetual inventory method), and M_{jt} as the real value of intermediate input expenditures.[35] Our main departure from the literature here is the choice of labor input L_{jt}, which we construct as the ability-

[31]We follow GNR in using a second-degree polynomial sieve estimator to obtain $D(k_{jt}, l_{jt}, m_{jt})$ from equation 13, which means this integral has a closed-form solution. See GNR and Chen (2007) for details.

[32]We assume the firm-specific function h_j varies across 2-digit industries, but is common across firms within industries. We estimate Ψ and h_j as complete second- and third-degree polynomials respectively.

[33]Our moments for the second-stage estimation are capital, squared capital, and lags of mean worker experience, worker tenure, worker age, market share, as well as lags of the share of workers in the firm who have with a college degree, have management positions in the firm, are white collar workers, and workers who were at the firm in the previous period.

[34]See section 3 in GNR on the non-identification of flexible inputs in production function estimation.

[35]This is consistent with the model assumptions on output and intermediate input markets and prices, where we deflate intermediate inputs and output by industry-year level price indices (P_t^Y and P_t^M). In practice, our measure of productivity is "revenue" TFP rather than "quantity" TFP and thus contains both variation in production efficiency, as well as potential (unmodeled) variation in output demand. We do not see this as a problem in our context, as we are agnostic about the source of the firm shock. We allow firms to adjust wages in response to shocks to both efficiency and demand, as both of these represent measures of firm-level risk that may be passed on to workers' wages. We choose to estimate revenue TFP since it allows us to include firms from the service sector, which accounts for most of Danish employment and economic activity.

units weighted sum of total hours: $L_{jt} = \sum_{i \in j} A_{it} H_{ijt}$. This way of measuring labor input has two main advantages. First, it does not impose homogeneous ability across workers or perfect competition in the labor market when estimating the production function. Second, it accounts for endogenous changes and cross-sectional differences in the ability composition of the labor force and peels it off from our estimates of firm-level productivity.[36]

This gives us a non-parametric estimate of the firm-level production function, as well as the firm-level distributions of ω_{jt}, η_{jt}, and ϵ_{jt}. It also allows us to estimate firm-level returns to scale, the marginal revenue product of labor, and therefore markdowns (μ_{jt}) for each firm in each period. We will use each of these elements in the discussion below.

4.3 Passthrough from TFP to Wages

Our estimates of the firm-level ability price W_{jt}, and the productivity shocks η_{jt} and ϵ_{jt}, allow us to then estimate the passthrough from TFP shocks to wages. The firm's FOCs imply that the period t solutions to the firm's maximization problem, $\{L^*_{jt}, \tilde{Z}^*_{jt}, M^*_{jt}, K^{I*}_{jt}\}$, are all functions of the variables in the information set at the beginning of period t. Therefore we can express the equilibrium wage W^*_{jt} as a function of these variables plus the transitory shock ϵ_{jt},

$$W^*_{jt} = f^W(K_{jt}, \overline{Z}_{jt}, P_t, \eta_{jt}, \epsilon_{jt}, L_{jt-1}, \tilde{Z}_{jt-1}), \tag{15}$$

or, in logs:

$$w^*_{jt} = \log f^W(\eta_{jt}, \epsilon_{jt}, K_{jt}, P_t, L_{jt-1}, \bar{Z}_{jt}, \tilde{Z}_{jt-1}). \tag{16}$$

[36]The most common approach to measure firm labor inputs is to use total hours of labor or the number of workers employed at the firm. Neither of these measures is ideal, however, as cross-sectional differences in the quality or composition of the workforce across firms will be loaded into productivity (ν_{jt}) and potentially bias our production function estimates. Similarly, changes in the quality of the firm's workforce, which our model suggests may be driven by productivity shocks, will also be interpreted as changes in ν_{jt}. For example, if a firm replaces full-time low-skill workers with full-time high-skill workers, the firm's output will likely go up, while the number of hours or employees will remain fixed. Another possibility is to use the total wage bill or the labor costs of the firm. In this case, a firm that uses more high-skill workers than low-skill workers will have a larger wage bill, potentially controlling for the difference in the ability of these types of workers. However, this approach implicitly assumes that wages are perfectly correlated with worker ability and that labor markets are perfectly competitive, neither of which is appropriate in our context.

The passthrough elasticities of interest are then:

$$\begin{aligned}
\varepsilon_\eta^W =& \frac{dw_{jt}}{d\eta_{jt}} = \frac{d}{d\eta}\log f^W(\eta_{jt},\epsilon_{jt},K_{jt},P_t,L_{jt-1},\bar{Z}_{jt},\tilde{Z}_{jt-1}) \\
\varepsilon_\epsilon^W =& \frac{dw_{jt}}{d\epsilon_{jt}} = \frac{d}{d\epsilon}\log f^W(\eta_{jt},\epsilon_{jt},K_{jt},P_t,L_{jt-1},\bar{Z}_{jt},\tilde{Z}_{jt-1}).
\end{aligned}$$

We can obtain estimates of the passthrough elasticity by approximating the (unknown) wage function in two ways, a log-linear approximation from which we can recover the average passthrough within our sample, and a polynomial approximation from which we can recover the full distribution of passthrough elasticities.

Log-linear approximation. First, we use a first degree approximation of equation 16 in changes:

$$\Delta w_{jt} = \alpha + \beta^\eta \eta_{jt} + \beta^\epsilon \epsilon_{jt} + \overline{X}_{jt}\Gamma + \beta^w w_{jt-1} + \delta_t + \varphi_{ijt}, \tag{17}$$

where $\overline{X}_{jt}$ includes logs of $\{K_{jt},\bar{Z}_{jt},\tilde{Z}_{jt-1},L_{jt-1}\}$. The parameter δ_t is a time-fixed effect that absorbs the contribution of the aggregate price vector and all other aggregate factors, and φ_{ijt} is measurement error. The estimates of β^η and β^ϵ then give us the *average* elasticity of passthrough from TFP shocks to wages. We do this primarily to compare our approach with other estimates in the literature which typically also obtain a scalar estimate for the average passthrough elasticity (for example, Garin and Silverio (2022) and Juhn *et al.* (2018)). We also use this specification to estimate average passthrough from changes in total TFP by replacing the $\beta^\eta\eta_{jt} + \beta^\epsilon\epsilon_{jt}$ terms with $\beta^\nu\Delta\nu_{jt}$. Finally, we interact all productivity terms with indicators for negative shocks, allowing us to separately identify passthrough from positive vs negative shocks.

Polynomial approximation. Second, we approximate equation 16 with a second degree polynomial with full interaction terms across all the variables in the wage function.[37] We then obtain the passthrough elasticities by taking the derivative of the log wage equation with respect to η_{jt} and ϵ_{jt}. Note that in this specification, we obtain a full distribution of firm-year passthrough elasticities. Specifically, using persistent shocks as an example, we have

$$\varepsilon_{\eta,jt}^W = \varepsilon_\eta^W(\eta_{jt},\epsilon_{jt},\overline{X}_{jt},w_{jt-1},\delta_t), \tag{18}$$

[37]Specifically, the full specification includes change in log wage as a function of all terms in equation 17, the square of each term in equation 17, as well as the multiplicative interaction between all terms, all in logs, as well as the lagged log wage.

where the passthrough elasticity ε_η^W is now indexed by subscript jt, varies across firms over time, and depends on the level of firm inputs, size of the shocks, and other variables in the firm's information set. Recovering the full distribution of passthrough elasticities allows us to examine both the conditional and unconditional relationships between passthrough and firm characteristics such as size and employment share.

In both approaches, the set of exogenous firm characteristics, $\overline{Z}_{jt}$, includes 2-digit industry and firm age. The set of endogenous firm labor-force characteristics, $\tilde{Z}_{jt}$, includes firm size (number of workers), the share of the firm in its local labor market (defined by a four digit industry/municipality cell), and the firm-level means of worker ability, experience and tenure. The vector $\tilde{Z}_{jt}$ also includes the share of workers who remained at the firm from the previous period, the share of employees who have a college degree, are in a management position, or are in a white collar occupation, along with indicator variables for each of these which equal one if the share is greater than zero.

Using the same methods, we decompose the passthrough from TFP shocks to wages into passthrough to the MRPL and passthrough to the markdown. That is, we replace the left hand side of equation 16 with the log of the MRPL or log markdown (obtained by estimating the production function) and estimate passthrough to both in the same fashion as passthrough to wages.[38]

5 Estimation Results

5.1 Wages, Productivity, and Markdowns

Our model estimates give us the distributions of firm-level ability prices (W_{jt}), worker level ability (A_{it}), the production function ($F(K_{jt}, L_{jt}, M_{jt})$), and the distributions of firm-level productivity (ν_{jt}), the persistent shock (η_{jt}), and the transitory shock (ϵ_{jt}). Knowledge of the production function also gives us the distributions of output elasticities for capital (ε_{Kjt}^Y), labor (ε_{Ljt}^Y) and materials (ε_{Mjt}^Y), returns to scale (RTS), the MRPL, and firm-level markdowns (μ_{jt}). We report key moments of each of these distributions in Table I.[39]

[38]Since we have $w_{jt} = \log \mu_{jt} + mrpl_{jt}$, we actually only have to estimate passthrough to two of the three terms, since differencing those estimates automatically gives us the third.

[39]We also report the means by 2-digit industry for these variables in Appendix Table A.7.

TABLE I – CROSS-SECTIONAL MODEL ESTIMATES

	Productivity			Wages and Markdowns			Output Elasticities			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ν_{jt}	η_{jt}	ϵ_{jt}	w_{jt}	$MRPL_{jt}$	μ_{jt}	RTS_{jt}	ε^{Y}_{Kjt}	ε^{Y}_{Ljt}	ε^{Y}_{Mjt}
Mean	0.00	0.01	-0.01	6.59	6.83	0.83	0.95	0.05	0.35	0.54
Std. Dev.	0.19	0.05	0.19	0.28	0.27	0.27	0.05	0.02	0.14	0.17
p10	-0.22	-0.05	-0.21	6.26	6.52	0.55	0.88	0.03	0.16	0.33
p25	-0.10	-0.02	-0.11	6.45	6.69	0.66	0.91	0.04	0.26	0.43
p50	0.01	0.01	-0.02	6.61	6.84	0.79	0.95	0.05	0.36	0.54
p75	0.10	0.03	0.08	6.76	6.98	0.94	0.98	0.06	0.45	0.66
p90	0.21	0.05	0.21	6.89	7.13	1.11	1.01	0.07	0.53	0.77
p99	0.52	0.12	0.57	7.27	7.52	1.85	1.08	0.10	0.68	0.91

Note: Table I shows cross sectional moments of the model estimates. The total number of firm-year observations is 374,000 rounded to the nearest thousand. Percentiles are calculated as the mean of the two adjacent milliles in order to avoid disclosing sensitive information. For example, to calculate the median of a variable, we divide the distribution into 1000 quantiles (milliles) and report the mean of the pooled 500th and 501st milliles.

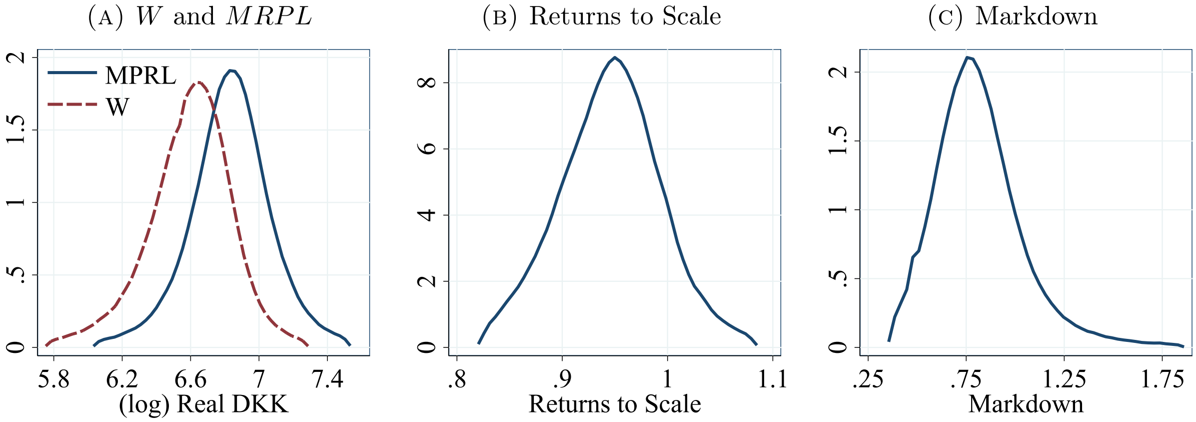
We find significant but comparatively low dispersion in firm level productivity and productivity shocks (columns 1-3). The p90/p10 TFP (ν_{jt}) ratio in our data covering the entire Danish private sector is 1.54, while other studies tend to find ratios of around 1.9 even within narrow manufacturing industries.[40] This is due to our approach in identifying worker heterogeneity separately from firm productivity. In fact, as we show in Table A.8 in the Appendix, the dispersion in measured firm productivity in our data increases significantly if we repeat the TFP estimation exercise without controlling for worker ability.[41] This is because worker ability is positively correlated with firm productivity and cross-sectional heterogeneity in labor force quality drives a significant portion of otherwise unexplained dispersion in firm outcomes.

We also find significant dispersion in the distribution of the (log) ability-adjusted hourly wage, $\log W_{jt}$. Firms at the 90th percentile pay about 70% higher wages conditional on worker ability than those at the 10th percentile. Despite being estimated using very different data, the distribution of the MRPL (column 5) is very similar to the firm-level wage distribution. The difference between these distributions (plotted in panel (a) of Figure 1) represents the log markdown, which we report in column 6 of

[40]For example, GNR find a mean p90/p10 ratio of 1.86 for 3-digit industries in the Colombian manufacturing sector, while Syverson (2011) reports an average ratio of 1.92 for 4-digit industries in the U.S. manufacturing sector.

[41]In particular, when we repeat the TFP estimation procedure using raw hours of labor as the labor input and report the resulting TFP distributions in appendix Table A.8. Relative to our baseline TFP measures, the uncorrected total TFP (ν^{L}_{jt}) distribution is 37% more disperse (standard deviation of 0.26 vs 0.19) while the persistent shock (η^{L}_{jt}) is 60% more disperse (standard deviation of 0.08 vs 0.05).

Figure 1 – Distributions of Firm-Level Wages, MRPL, RTS, and Markdowns



Note: This figure shows density plots of firm-level outcomes on a sample of about 374,000 firms-year observations. Density plots exclude the top and bottom percentiles of their respective distributions.

Table I. We find that the median firm pays workers 79% of their marginal product. The majority of firms (about 82%) have markdowns of less than one. However, 18% of firms pay workers more than their MRPL (panel (c) of Figure 1). Other papers which estimate markdowns have found a similar (or larger) proportion of markdowns greater than one, but have difficulty rationalizing the finding as their empirical and theoretical approaches generally do not admit adjustment or other employment costs.[42]

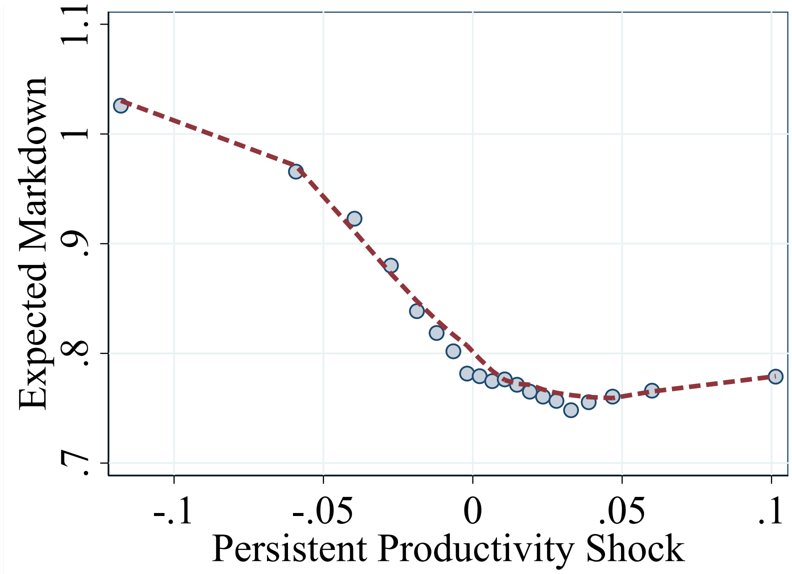
In contrast, in our model firms can set wages above the MRPL for two reasons. First, if the expected future marginal benefit of labor is greater than the current marginal cost of labor ($\frac{\partial \Phi}{\partial L_{jt}} < \frac{\partial}{\partial L_{jt}} \overline{V}_{jt+1}$), firms are constrained and may set wages higher than the MRPL in order to keep workers in the firm to reap those expected future continuation values. Second, transitory shocks may push worker wages above the firm's MRPL. To separate these effects, we construct the expected markdown prior to observing ϵ_{jt}:[43]

$$\overline{\mu}_{jt} = \frac{\varepsilon^{L}_{Wjt}}{1+\varepsilon^{L}_{Wjt}} \left(1 - \left(\frac{\partial \Phi_{jt}}{\partial L_{jt}} - \frac{\partial \overline{V}_{jt+1}}{\partial L_{jt}}\right) \overline{MRPL}_{jt}^{-1}\right). \tag{19}$$

[42] Yeh *et al.* (2022) obtain a median inverse markdown of 1.364 (which is a markdown of 0.73) in the US manufacturing sector, with an interquartile range of 0.6 and standard deviation of 0.7, implying a significant share of firms with markdowns greater than one. Brooks *et al.* (2021) obtain a median inverse markdown of 0.51 (a markdown of 1.96) using Indian data, implying that the median firm pays workers twice their marginal product.

[43] Since all terms involving ϵ_{jt} enter the wage function multiplicatively, we can directly estimate $f^c(\epsilon_{jt})$ and $\mathcal{E}^c \equiv E[f^c(\epsilon_{jt})]$ and set $\overline{\mu}_{jt} = \mu_{jt} \frac{\mathcal{E}^c}{\mathcal{E}} \frac{e^{\epsilon_{jt}}}{f^c(\epsilon_{jt})}$. See Appendix B.4 for details.

Figure 2 – Expected Markdown ($\overline{\mu}_{jt}$) by Shock Size

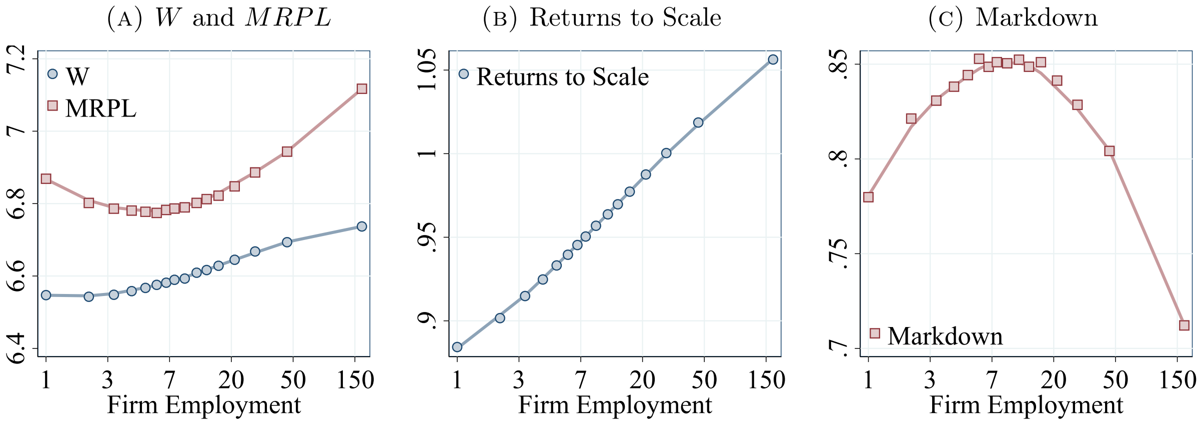


Note: This figure shows the average expected markdown (i.e., the markdown less the component due to the ex-post shock) by quantiles of the persistent productivity shock η_{jt}. Each dot represents the mean of roughly 18700 observations.

We find that 16% of firms have $\overline{\mu}_{jt} > 1$, suggesting that ex-post wage adjustment accounts for 11% (i.e.: 2/18) of those markdowns greater than one with the remainder being due to adjustment costs. Intuitively, firms that are hit with a large negative persistent productivity shock (and thus experience a significant declines in MRPL through the direct effect in equation 8) would prefer to reduce their labor input and scale production down, lower wages, and increase the MRPL. However, if faced by significant downward adjustment costs and sufficiently high expected future productivity, these firms may instead find it optimal to keep their labor input above the level which would be optimal if labor were a flexible input. We confirm this intuition in Figure 2 where we plot the mean of $\overline{\mu}_{jt}$ across quantiles of the η_{jt} distribution. Average markdowns for firms with positive shocks do not differ by shock size and are uniformly below one. However, firms experiencing negative shocks see increasing (narrowing) markdowns. Very large negative shocks are associated with average markdowns greater than one. We show further evidence that firms face substantial adjustment costs in the subsequent sections.

While we cannot directly observe the adjustment cost terms without applying further structure to the model, we can use the existing model structure to estimate the labor supply elasticities and thus the relative contribution of market power to markdowns

Figure 3 – Correlation of Wages, $MRPL$, RTS, and Markdowns with Firm Size



Note: This figure shows binscatter plots of firm-level outcomes by firm employment groups based on a sample of approximately 374,000 firms-year observations. Wages and MRPL are in logs, while returns to scale and markdowns are in levels.

and wage setting. To do this, we directly nonparametrically estimate the labor supply function, $L_{jt} = L(\overline{W}_{jt}, \overline{Z}_{jt})$ and recover the firm-level distribution of labor supply elasticities $\varepsilon_{\frac{L}{W}_{jt}}$. We address the potential correlation between wages and unobserved labor supply shifters by using a natural set of demand shifters arising from our model (firm productivity) as instruments. The mean labor supply elasticity is 2.7, which implies (in the absence of adjustment costs) a mean markdown of 0.73.[44] Since the actual mean markdown is 0.83, we conclude that most firms are constrained by adjustment costs and tend to over-employ (hoard) labor as a result.[45] Similarly, the presence of adjustment costs leads workers to earn significantly (14%) more of their marginal product than they would in a world without such adjustment costs.[46]

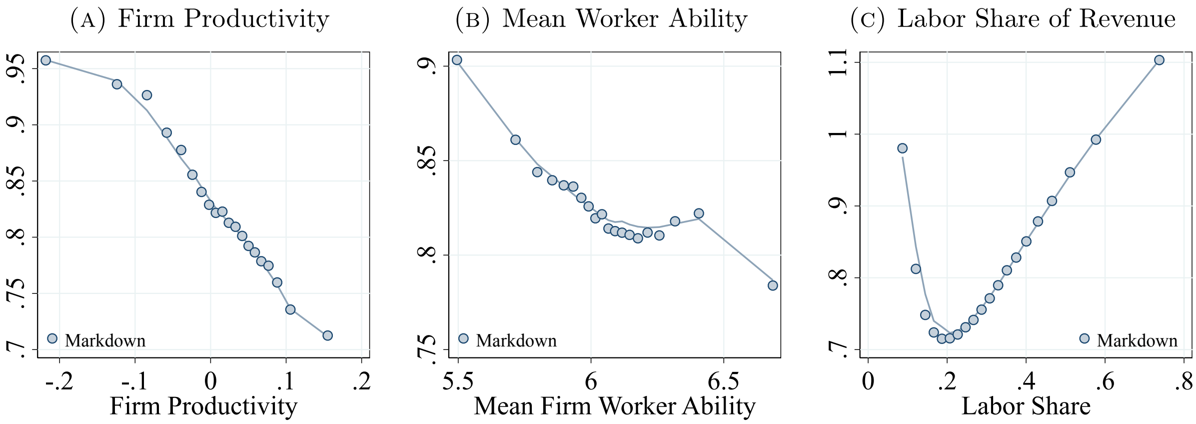
We plot the relationship between wages, MRPL, markdowns and firm size in Figure 3. While (log) wages are positively correlated with firm size, the (log) MRPL has a u-shaped relationship. Unlike other studies (e.g.: Yeh *et al.* (2022)), we find that markdowns do

[44]We use several different strategies and find broadly similar results. Our estimated labor supply elasticities are also consistent with theory, decreasing in firm market share and increasing in our measure of the markdown. See Appendix B.5 for estimation details and further results. Seegmiller (2021) gets remarkably similar mean labor supply elasticities and markdowns in a parametric model calibrated using data on US firms. See Sokolova and Sorensen (2021) for an overview of the literature.

[45]This implies that the second (bracketed) term in equation 19 is greater than one on average, and so the marginal non-wage cost of labor is lower than the marginal expected future value. This means firms are employing more labor than they would absent adjustment costs.

[46]Our model implicitly assumes that unobserved firm job amenities are uncorrelated with (shocks to) TFP. To the extent that these are positively correlated, our estimates represent an upper bound on the labor supply elasticities, and so our intuition about the effect of adjustment costs on wage setting represents a lower-bound. See Seegmiller (2021) for a discussion of this issue in a related setting.

FIGURE 4 – CORRELATION OF MARKDOWNS WITH PRODUCTIVITY, LABOR SHARES, AND WORKER ABILITY



Note: This figure shows binscatter plots of firm-level markdowns by equal-sized groups of firm productivity (ω_{jt}), labor share of revenue, and mean worker ability, based on a sample of approximately 374,000 firms-year observations. Productivity and worker ability are in logs, while labor shares and markdowns are in levels.

not have a monotone relationship with size. Medium sized firms with 5 to 20 employees have the narrowest markdowns, paying 85% of MRPL on average, while smaller and larger firms tend to have wider markdowns. Firms with more than 100 employees have the widest markdowns, paying only around 71% of MRPL on average. In fact, the employment (and revenue) weighted mean markdown is 0.7, suggesting that most workers only get paid slightly more than 2/3rds of their marginal product.[47]

To further study what drives variation in market power, we plot the relationship between markdowns and productivity, worker ability, and the labor share of revenue in Figure 4. More productive firms, and firms with high average worker ability, tend to have low markdowns.[48] This has strong implications for the distributional effects of anti-trust policy applied to labor markets, as a broad reduction in firm-level labor market power may disproportionately benefit high wage, high ability workers and increase wage inequality. Markdowns have a U-shaped relationship with the firm's labor share of revenue. Labor market power generally decreases as labor becomes more important in a

[47] These markdowns have been narrowing over time as firm-level ability-adjusted wages in Denmark have been increasing. Appendix Figure A.4 plots growth in w_{jt} over time, where we have normalized the first year to 0. We see growth of 0.232 log points, or 26% over 10 years. We also plot the normalized growth of the log markdown and log MRPL. The average MRPL has increased by 0.084 log points, which is substantial, but most of the growth in average wages has come from a dramatic narrowing of the (unweighted) average markdown – from 0.766 in 2001 to 0.892 in 2010 (0.148 log points). Danish workers received much more of their marginal product in 2010 than in 2001.

[48] This negative relationship is even stronger between markdowns and the MRPL, though markdowns are still positively correlated with the wage as we show in Appendix Figure A.5.

firm, though this doesn't hold for firms with small labor shares.[49]

The last 4 columns of Table I report the returns to scale and output elasticities. Our output elasticities are in line with production function estimation literature and give us a mean returns to scale of 0.95 with a standard deviation of 0.05.[50] About 13% of our firms have returns to scale greater than one, but while our output elasticities display significant dispersion across firms (greater than returns to scale), none in our sample lie above one, implying strictly decreasing returns to each input. We find that output is much more sensitive to changes in materials than labor, suggesting that the materials input passthrough channel discussed in section 2.2 may dominate the labor input channel for most firms (a fact which our passthrough to MRPL results will confirm). Figure 3 shows that larger firms tend to have much greater returns to scale.

5.2 Passthrough from Firm Shocks to Wages

Table II displays our baseline results for average passthrough from estimating equation 17. Column 1 shows the average passthrough from changes in total TFP, $\Delta\nu_{jt}$, whereas column 2 shows the passthrough elasticity for positive and negative changes in total TFP. We find that, on average, firms pass 32.0% of total TFP changes to workers' (ability adjusted) hourly wages. The effect of a positive TFP change on wages is higher than the effect of a negative change, with firms passing 39.7% of positive changes in TFP to wages, but only a 25.4% of negative to wages, suggesting that firms provide some degree of insurance against negative shocks to their workers.

Columns 3 and 4 show the results from estimating equation 17 for shocks to the persistent and transitory components of productivity, η_{jt} and ϵ_{jt}. We find that on average, firms pass 37.8% of persistent shocks to wages. This also hides significant asymmetry in the passthrough. The passthrough from persistent shocks is positively asymmetric, comparing 42.0% from a positive shock to 31.8% passthrough from negative shocks.[51]

[49] Part of this correlation comes from the fact that highly productive firms tend to have lower labor shares. See Appendix Figure A.5.

[50] For example, GNR find average capital, labor, and intermediate output elasticities of 0.16, 0.38 and 0.55 in Colombia and 0.14, 0.35 and 0.54 in Chile. These are very similar to ours, despite the fact that GNR only use manufacturing firms, treat labor as predetermined, and do not adjust for labor quality.

[51] All of these results are statistically and economically significant and represent a large variation in firm-level wages. For example, given a passthrough elasticity equal to 0.32 and a mean hourly wage of \$38 (in 2010 USD with an exchange rate of 5.6), a one standard deviation change in firm TFP implies a \$2.30 change in hourly wage or a \$3,834 change in yearly income for a full-time worker. These passthrough estimates are significantly larger than most previous estimates using firm-level wages and

Table II – Passthrough from TFP to Wages

	Δw_{jt}				Δmrpl_{jt}		$\Delta \log \mu_{jt}$	
	Level	Pos/Neg	Level	Pos/Neg	Level	Pos/Neg	Level	Pos/Neg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\nu_{j,t}$	0.320							
	(0.002)							
$\Delta\nu > 0$		0.397						
		(0.004)						
$\Delta\nu < 0$		0.254						
		(0.004)						
η			0.378		2.106		-1.728	
			(0.006)		(0.006)		(0.009)	
$\eta > 0$				0.420		2.277		-1.858
				(0.011)		(0.010)		(0.015)
$\eta < 1$				0.318		1.950		-1.632
				(0.011)		(0.010)		(0.014)
ϵ			0.289		0.965		-0.677	
			(0.003)		(0.003)		(0.004)	
$\epsilon > 0$				0.261		0.958		-0.697
				(0.004)		(0.003)		(0.005)
$\epsilon < 0$				0.314		0.970		-0.656
				(0.004)		(0.003)		(0.005)
R^2	0.240	0.241	0.241	0.241	0.477	0.478	0.297	0.297
Number of Observations: 374,000								

Note: Table II shows the regression coefficients for a series of firm-level panel regressions. Each regression includes year and industry-fixed effects and a series of firm-level controls such as firm age, firm size, and characteristics of the workforce (average tenure, average estimated ability, share of white collar workers). Observations rounded to the nearest thousand.

We then decompose passthrough to wages into the passthrough to the firm's MRPL and the passthrough to markdowns. We obtain the average passthrough to each by running the same regression as for passthrough to wages, but replacing the dependent variable with changes in (log) MRPL and markdowns. Column (5) of Table II shows that a 1% increase in persistent productivity leads to a 2.11% increase in the MRPL. This means that the material channel in equation 8 is positive and greater than one, that the MRPL increases with materials, and that this increase dominates the negative effect of the labor channel on the marginal product and the wage. We can also conclude that demand for materials is very elastic to persistent productivity shocks relative to

value-added or output shocks. In a recent review, Card *et al.* (2018) report that the average elasticities estimated by such papers range from 0.02 to 0.29. This is compared to the average passthrough of 0.38 we find from persistent shocks. We discuss why the rest of the literature finds lower estimates later in this section.

labor, which is consistent with the assumptions that M_{jt} is a flexible input which does not face adjustment costs, while L_{jt} is subject to significant adjustment costs. Models and empirical frameworks built on value-added production functions cannot account for this key component of passthrough and wage setting.

Column 7 shows that the passthrough of η_{jt} to markdowns is negative, as predicted, and also very high. A 1% increase in persistent productivity leads to a 1.73% decrease (widening) of the firm's markdown. This is due to a combination of a decreasing labor supply elasticity (as firms move up their labor supply curve), and an increase in the cost of employing those workers relative to the expected future gains from their employment.[52]

The average passthrough from transitory shocks (ϵ_{jt}) is somewhat lower at 28.9% and negatively asymmetric, with an estimate of 26.1% for positive and 31.4% for negative shocks. Firms do not adjust their input choices after a transitory shock ϵ_{jt} by assumption, so the passthrough from transitory shocks have different implications relative to persistent shocks. The model implies that passthrough of ϵ_{jt} to the MRPL is equal to 1, while the passthrough to markdowns is determined entirely by the bonus function:

$$\frac{\mathrm{d}\log \mu_{jt}}{\mathrm{d}\epsilon_{jt}} = \frac{\partial}{\partial \epsilon_{jt}} \log f^c(\epsilon_{jt}) - 1. \tag{20}$$

We find a (roughly symmetric) passthrough from ϵ_{jt} to the MRPL of 0.97 (column 5), which is very close to our model prediction. We conclude that the negative asymmetry of the wage passthrough result is due entirely to the asymmetric passthrough of transitory shocks to markdowns. Here, we find an average passthrough of -0.68, with positive shocks decreasing (widening) the markdown by 0.70 and negative shocks increasing (narrowing) the markdown by 0.66. From equation 20 we then know that $\partial \log f^c / \partial \epsilon_{jt} = 0.32$, or 0.3 for positive shocks and 0.34 for negative shocks, implying that $f^c(\epsilon_{jt})$ is concave. This is consistent with our direct estimates of $f^c(\epsilon_{jt})$ in Appendix B.4. Firms are more likely to temporarily set wages below their expected value after a negative transitory shock than above expectations after a positive transitory shock.

We report key cross-sectional moments derived from our flexible approach to estimating the firm-level distribution of passthrough elasticities (equation 18) in Table III.[53] Although the the mean elasticities are very similar to our linear approach, we find signif-

[52] By construction, the relationship between wages, markdowns and the MRPL imply that column 3 is the sum of columns 5 and 7, and likewise for 4, 6 and 8.

[53] Appendix Figure A.6 shows the full cross sectional distribution of each variable.

Table III – The Distribution of Passthrough Elasticities

Variables	Mean	St. Dev.	p10	p25	p50	p75	p90	p99
ε_{η}^{W}	0.356	0.178	0.147	0.237	0.346	0.464	0.582	0.831
$\varepsilon_{\eta}^{MRPL}$	2.205	0.614	1.516	1.815	2.143	2.538	2.987	3.984
ε_{η}^{μ}	-1.849	0.548	-2.564	-2.146	-1.789	-1.488	-1.232	-0.715
Number of Observations: 374,000								

Note: Table III shows the cross sectional moments of the firm-level elasticities of wages, MRPL, and markdowns with respect to η. Observations rounded to the nearest thousand. All percentiles are the mean of two adjacent milliles.

icant dispersion in passthrough across firms due to variation in production technology, market power, and adjustment costs.[54] In subsequent sections, we use this heterogeneity to investigate the mechanisms behind passthrough and wage setting.

Passthrough Using Other Measures of Firm Shocks. A key contribution of this paper is to model how firms set wages in response to changes in their fundamental productivity, and to show how these productivity shocks can be identified in the presence of endogenous firm inputs and unobserved worker ability. This is in contrast to the bulk of the literature on rent sharing and passthrough of firm shocks to wages, which generally proxies firm shocks using value-added or profits per worker or other similar measures of firm performance.[55] Because these measures of firm performance are themselves endogenous functions of the underlying productivity process, as well as the passthrough mechanisms we have discussed so far, measuring their correlation with wages may result in estimates of passthrough which do not represent the true relationship between firm-level risk, rent-sharing and wages. This is true even if the research design includes successful corrections for omitted variable bias (as in Kline *et al.* (2019) or other papers which use instruments for firm shocks). Similarly, measuring firm performance using structural measures of productivity without controlling for unobserved variation in labor quality also results in biased estimates of the passthrough elasticity, as changes in productivity will be conflated with endogenous changes in labor quality at the firm.

To assess how our measure differs from and contributes to the existing literature, we

[54] In a model without these frictions and without production heterogeneity, these distributions would collapse to a single point. See Section 6.2 and Appendix B.3 for further discussion.

[55] The most common method, used by papers such as Guiso *et al.* (2005), Fagereng *et al.* (2017), Juhn *et al.* (2018), Card *et al.* (2018), and Friedrich *et al.* (2019) is to use a (sometimes residualized) measure of value-added or value-added per worker. Similarly, Berger *et al.* (2022) consider value-added per worker shocks when they measure passthrough in their structural model.

Table IV – Passthrough Across Different Definitions of TFP

	Baseline $\Delta\nu$	Baseline η	TFP $\Delta\nu^L$	Value Added $\Delta\nu^{VA}$		MRPL $\Delta mrpl$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Elasticity	0.313	0.369	0.522	0.066	0.126	0.191	0.139
	(0.002)	(0.006)	(0.002)	(0.001)	(0.001)	(0.002)	(0.004)
R^2	0.235	0.236	0.305	0.211	0.239	0.216	0.213
Ability	Yes	Yes	No	Yes	No	Yes	Yes
2SLS	No	No	No	No	No	No	Yes
Number of Observations: 368,000							

Note: Table IV shows the regression coefficients from a series of firm-level panel regressions for different definitions of firm shocks. The "Ability" row indicates whether the LHS variable was Δw_{jt} ("Yes") or change in mean hourly wage without ability controls ("No"). The "2SLS" row indicates whether the firm shock variable was instrumented by η_{jt} ("Yes") or not. Each regression includes year and industry-fixed effects and a series of firm-level controls such as firm age, firm size, and characteristics of the workforce (average tenure, average estimated ability, share of white collar workers). Number of observations rounded to the nearest thousand. Columns (1) and (2) re-calculate our main results using a reduced sample that is consistent across all specifications.

run variations of our baseline log-linear regression (equation 17) using several alternative measures of firm performance and show the results in Table IV. The first two columns are the average passthrough from $\Delta\nu_{jt}$ and η_{jt} and reproduce our baseline results of section 5. To show the importance of controlling for unobserved labor quality, we estimate a measure of productivity (ν_{jt}^L) using the same procedure as described in section 4.2 with the only difference being that the labor input is set to the total number of hours of labor without weighting by ability, i.e.: $L_{jt} = H_{jt}$. We find that failing to correct for worker ability (shown in the third column) biases our passthrough elasticity up to almost double the baseline result (0.522 versus 0.313).[56] The reason for this bias is intuitive. Without controlling for unobserved ability, our left-hand side variable is the mean wage within the firm, or $E[A_{it}W_{jt}]$. This will be correlated both with ν_{jt}^L and with unobserved ability, which is now also present in the residual on the right-hand side. This leads to omitted variable bias, where changes in productivity are positively correlated with unobserved ability, both of which are positively correlated with the mean wage.

We then evaluate the importance of using an exogenous measure of firm productivity rather than endogenous measures such as value-added when studying passthrough. To do this, we replace the measure of productivity with changes in value added per

[56]Specifically, the third column uses the uncorrected measure of productivity ν_{jt}^L instead of ν_{jt}, and uses the mean individual hourly wage at the firm as our measure of the wage instead of the ability price we recover from our two-sided fixed effect model. In this alternate regression we additionally exclude the measure of average worker ability from $\tilde{Z}_{jt-1}$.

worker (other variables are unchanged from the baseline) in column 4, and in MRPL in column 6.[57] The results show that using endogenous measures of firm performance drastically under-estimates true passthrough from productivity to wages. This is because firms adjust labor and material inputs in response to productivity shocks, which changes the MRPL (and value added per worker). When one estimates the passthrough from the MRPL to wages, this endogenous response is missed. Because the change in MRPL is much greater than the underlying change in productivity (our estimated average passthrough to the MRPL above is 2.1), the responsiveness of wages to the MRPL will be much smaller than the true responsiveness of wages to the underlying productivity shock. Since productivity and the MRPL are positively correlated, using instruments for the MRPL or value added to correct for unobserved productivity will actually decrease the passthrough estimates further. We show this in column 7 of Table IV, where we run the same regression as column 6, but instrument the change in log MRPL with η_{jt}, our "true" measure of the exogenous change in productivity. As expected, average passthrough declines from 0.19 to 0.14.

Lastly we repeat the previous exercises by removing both the ability-adjusted wage and using value added per-worker instead of TFP shocks. Confirming our intuition about the direction of the biases, the average passthrough elasticity from value-added to the mean wage is 0.126 (column 5), which is biased up relative to the exercise with value-added and ability-adjusted wages, and biased down relative to our estimates with structural measures of productivity. This specification is most closely related to the measures of passthrough in much of the literature, and the estimate we get from this specification closely matches what these other papers find (see Card *et al.* (2018)). This emphasizes the importance of correcting both for the endogeneity of firm inputs, and unobserved labor quality, when estimating the link between wage setting and firm shocks.

Passthrough of Aggregate Shocks. We examine how passthrough differs for aggregate vs idiosyncratic shocks, by constructing measures of annual economy-wide shocks, industry-level shocks, and idiosyncratic shocks following Carlsson *et al.* (2015) and estimating passthrough from each. In particular, we project η_{jt} onto a set of year indicator variables, which gives us the average annual persistent change in productivity. We then take the residuals from this procedure and project them on a full set of industry-year

[57] Note that in a model with a log-linear production function (such as a Cobb-Douglas), the MRPL and value-added/output/revenue per worker (depending on how output is defined) are equivalent up to a constant, while in our flexible framework this will generally not be true.

Table V – Passthrough Elasticities Across Different Shocks

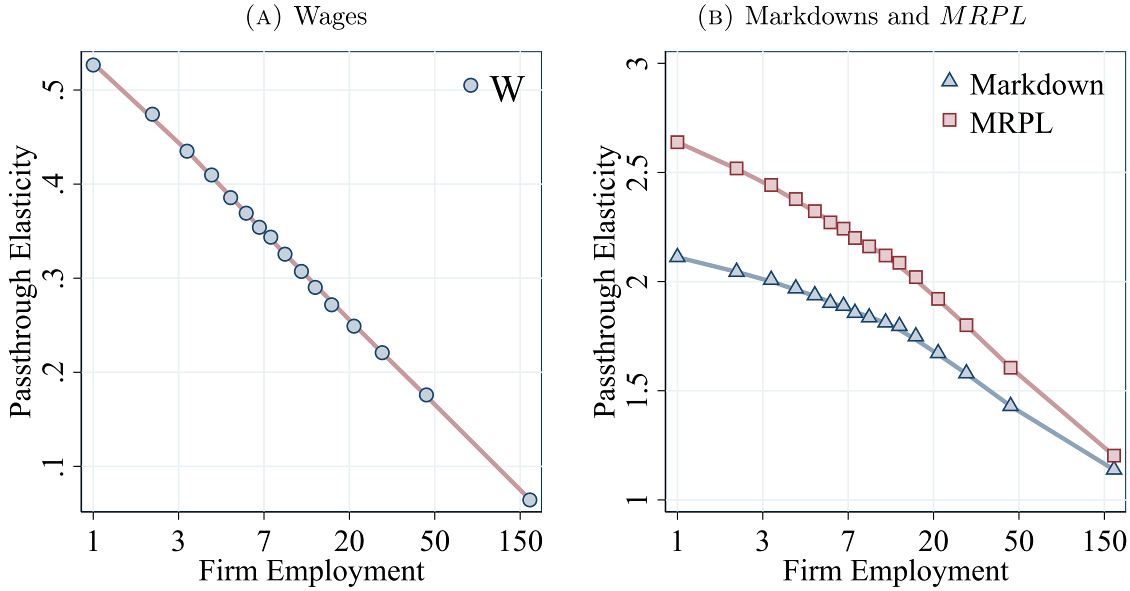
Variables	Δw_{jt} (1)	Δmrpl_{jt} (2)	$\Delta \log \mu_{jt}$ (3)
Idiosyncratic shocks	0.425	2.256	-1.731
	(0.007)	(0.006)	(0.009)
Industry shocks	0.074	1.071	-0.997
	(0.020)	(0.018)	(0.027)
Aggregate shocks	1.175	1.140	0.035
	(0.047)	(0.043)	(0.064)
R^2	0.235	0.470	0.285

Note: Table shows the passthrough elasticity of wages, MRPL and markdowns with respect to the idiosyncratic shocks, industry level shocks, and aggregate shocks. This analysis includes all controls in our baseline analysis. Number of observations rounded to the nearest thousand.

indicator variables, providing industry-level productivity shocks. The residuals from this last procedure are purely idiosyncratic firm-level shocks to productivity. We estimate passthrough to wages, markdowns and the MRPL for each and present the results in Table V. Passthrough from the residualized idiosyncratic component of η_{jt} is similar to our baseline results. Passthrough of industry-level shocks is very small, at 0.07. This is due to passthrough to markdowns and the MRPL both being almost exactly 1 in absolute value and much smaller than passthrough of idiosyncratic shocks.

Intuitively, while individual firms face elastic short run material supply curves, this curve is much less elastic at the industry level. This leads the labor and materials channels to cancel each other out in passthrough to the MRPL (equation 8), leaving only the direct effect. Passthrough to the markdown is also smaller because, while increased industry productivity increases relative industry employment, this effect is weaker than the within-industry effect, suggesting that firm-level labor supply elasticities are higher than industry-level elasticities. At the aggregate (national) level, passthrough to the MRPL is slightly greater than 1, and there is no passthrough of aggregate shocks to firm-level markdowns. This likely reflects that the national-level labor supply curve is almost perfectly inelastic in the short run, so aggregate shocks affect the labor channel even less than the materials channel in passthrough to the MRPL. Similarly, since an aggregate shock does not change relative market shares in the short run, we see no passthrough to markdowns. These results suggest that market power plays a significant role in driving passthrough from idiosyncratic shocks, but not aggregate shocks.

Figure 5 – Passthrough by Firm Size



Note: This figure shows binscatter plots the average passthrough to firm-level markdowns (in absolute value), MRPL, and wages from a persistent shock to firm TFP, η_{jt}, within firm size groups, based on a sample of approximately 374,000 firms-year observations. The values on panel (a) for each firm employment bin are equal to the *difference* between the average MRPL and markdown values for each bin on panel (b).

5.3 Firm Size, Market Share, and Passthrough

Using the polynomial approximation method described in section 4.3, we recover the entire distribution of passthrough elasticities for all firms in each year, which allows us to examine how passthrough varies across different dimensions of firm heterogeneity and use this variation to learn about the underlying mechanisms. For example, more productive firms tend to be bigger and account for a larger share of labor and other input markets than less productive firms. Does this translate into more or less passthrough from TFP shocks to wages? As discussed earlier, a standard oligopsonistic model of labor supply and competition predicts that larger firms will have less passthrough to wages. This is consistent with what we find in the data.

Figure 5 shows that passthrough to wages is negatively correlated with firm employment level. Small companies pass a significantly larger proportion of productivity shocks to wages than large companies (panel a), especially relative to those with 100 workers or more, for which the passthrough elasticity is less than 0.1 on average. This suggests that worker level passthrough elasticities are significantly lower than firm level passthrough elasticities on average, since the majority of workers work at large firms.[58] This decline in the passthrough elasticity is due to a decline in the *difference* between the passthrough to MRPL and markdowns, shown in panel (b) of Figure 5.

Interestingly, the presence of oligopolistic labor market power predicts that passthrough to the MRPL and markdowns should *increase* in absolute value for larger firms.[59] We find the opposite, with larger firms adjusting their MRPL and markdowns in response to productivity shocks much less than smaller firms. This is also true if we look at how passthrough varies across labor market shares.[60] This decomposition shows that oligopsony power in labor markets cannot be the sole driver of passthrough and wage setting. Instead, we find patterns that are consistent also with the presence of adjustment costs and production heterogeneity, suggesting that all three mechanisms play an important role. We explore the relative contributions and importance of these mechanisms in the next section.

6 Passthrough Heterogeneity and Mechanisms

In our model, cross-sectional differences in passthrough and wage setting are driven by three mechanisms: heterogeneity in production technology, labor market power, and adjustment or employment costs. However, our model also nests the possibility that none of these factors play a role in wage setting—i.e., that firms have common (e.g.: Cobb-douglas) output and substitution elasticities, common labor supply elasticities, and no adjustment costs. In this section, we test this null-hypothesis by examining how passthrough varies across different indicators of these mechanisms. We then measure the relative importance of each mechanism by estimating counter-factual passthrough elasticity distributions under different restrictions on the model.

6.1 Evidence of the Mechanisms

The Role of Technology. Our model predicts that firms with higher materials output elasticities should have higher passthrough to wages, whereas firms with higher labor

[58] Using similar data and methods, Chan *et al.* (2022) find an average worker-level passthrough elasticity in Denmark of 0.08.

[59] See section 2.2 and Appendix B.3 for discussion and details.

[60] We show the relationship between labor market share and our passthrough elasticities in Appendix Figure A.7. To get a firm-level measure of labor market share, we define a labor market as a municipality and 4-digit industry pair and calculate the share of workers at each firm within each market. Since firms often operate in multiple municipalities, we then take the average share for each firm across all the markets in which it operates (in each year) and use this as our measure of firm labor market share.

output elasticities should see less (see equation 8). To see whether is the case, we regress the firm level passthrough elasticity on lagged firm output elasticities. Intuitively, if heterogeneous technology plays no role (as with a Cobb-Douglas production function), then we should find little or no relationship between output elasticities and the passthrough. Panel A in Table VI shows results from univariate regressions (columns 1 to 3) of the firm-time-level wage, markdown and MRPL passthrough elasticities on the firm-time-level output elasticities. We find the output elasticities of material and labor are both negatively correlated with the passthrough elasticity. This is likely because larger firms have both lower passthrough (Figure 5), greater output elasticities, and higher returns to scale (Figure 3). We control for this in columns 4 to 6 by including firm characteristics (i.e., lags of productivity, size, capital and firm age) and firm-level fixed effects in the regression. We see that the coefficients from the wage passthrough elasticity regression on the labor output elasticity remains negative while those on the material output elasticity coefficient become positive as expected. We conclude that heterogeneity in production technology across firms and time is a significant driver of wages and passthrough.

The Role of Market Power. We use the same approach to examine the role of labor market power in wage setting and passthrough. Here our measures of market power are the (firm-time) labor market share (defined in section 5.3) and an industry-level market concentration measure which we construct as the Herfindahl-Hirschman Index of firm shares of the total labor cost (wages plus pension contributions) within a 4-digit industry in a given year. Firms with higher employment shares, or which operate in industries which are more concentrated in terms of labor costs, are more likely to operate with greater market power and face lower labor supply elasticities (Figure A.3). We showed previously that average passthrough to wages is declining in firm size and labor market share, which is consistent with both our flexible model and standard parametric oligopsonistic models of labor market competition such as in Manning (2021), Chan *et al.* (2021), and Berger *et al.* (2022). However, while our theory predicts that passthrough to the MRPL and markdown are increasing (in absolute value) in size and market share, we show in Figure A.7 and panel B of Table VI that the unconditional relationship is the opposite.[61] Once we control for firm characteristics (including lagged firm size) in columns 4 to 6, we find that the signs for passthrough to markdowns and the MRPL

[61] We also construct measures of concentration using revenue shares and employment shares and find very similar results.

Table VI – Passthrough Mechanisms

	Univariate Regressions			Multivariate Regressions		
	(1)	(2)	(3)	(4)	(5)	(6)
	ε_{η}^{W}	ε_{η}^{μ}	$\varepsilon_{\eta}^{MRPL}$	ε_{η}^{W}	ε_{η}^{μ}	$\varepsilon_{\eta}^{MRPL}$
Panel A: The Role of Technology						
ε_{M}^{Y}	-0.193	-0.732	0.540	0.059	-1.043	1.102
	(0.002)	(0.005)	(0.006)	(0.003)	(0.009)	(0.009)
R^2	0.033	0.049	0.021	0.835	0.840	0.884
ε_{L}^{Y}	-0.075	1.651	-1.726	-0.110	1.896	-2.006
	(0.002)	(0.006)	(0.007)	(0.003)	(0.010)	(0.010)
R^2	0.004	0.181	0.157	0.836	0.851	0.893
Panel B: Labor Market Power						
Market Share	-0.245	-0.009	-0.236	-0.102	-0.161	0.058
	(0.001)	(0.004)	(0.004)	(0.001)	(0.005)	(0.004)
R^2	0.113	0.000	0.009	0.838	0.833	0.877
Market Concentration	-0.300	0.346	-0.646	-0.046	-0.174	0.127
	(0.003)	(0.010)	(0.011)	(0.002)	(0.009)	(0.009)
R^2	0.023	0.003	0.009	0.492	0.188	0.337
Panel C: Adjustment Costs						
Mean Tenure	-0.077	0.139	-0.215	-0.095	0.031	-0.126
	(0.000)	(0.001)	(0.0021	(0.001)	(0.002)	(0.002)
R^2	0.087	0.029	0.057	0.847	0.832	0.878
Labor Churn	0.363	-1.431	1.794	0.255	-1.318	1.573
	(0.003)	(0.008)	(0.009)	(0.002)	(0.008)	(0.008)
R^2	0.046	0.074	0.093	0.512	0.247	0.405

Note: Table VI is from a series of univariate (columns 1 to 3) and multivariate (columns 4 to 6) firm-level panel regressions of passthrough elasticities on (lagged) firm characteristics. The additional controls included in the multivariate regressions are: Lagged persistent firm level productivity (ω_{jt-1}), log firm size, log capital, firm age, and firm-level fixed effects, except in the market concentration and labor churn regressions where we exclude the fixed effect. This is because concentration and churn are measured at the industry and market level and are thus swept up by the fixed effects, leaving us with little to no identifying variation.

have flipped, as is consistent with our theoretical predictions.[62]

The Role of Adjustment Costs. In section 5.1 we show that adjustment costs likely play a significant role in wage setting. To study their impact on passthrough, we analyze the relationship between estimated passthrough elasticities and two proxies of labor adjustment costs. The first proxy is the average tenure of workers employed at a firm,

[62] See the fifth exercise in Appendix B.3 where we explore a case when firms are not atomistic and the labor supply elasticity is an endogenous function of firm size (as in Berger *et al.* (2022) and Chan *et al.* (2021)).

which reflects higher costs of employee turnover.[63] Firms facing higher costs adjust labor inputs (and thus wages) less in response to productivity shocks, leading to lower passthrough. Our second proxy for adjustment costs is employment churn in the labor market.[64] Higher churn indicates lower adjustment costs. The bottom two panels of Table VI show our results. Overall we find that firms with higher average worker tenure (high adjustment costs) exhibit lower overall passthrough to wages, while firms in markets with high churn (lower adjustment costs) have higher passthrough.

We find further evidence that adjustment costs play an important role in wage setting and passthrough by looking at how wage setting responds to shocks of different sizes and direction. The presence of adjustment costs may generate differential passthrough for positive and negative shocks (as we find in Table II), and very different responses to large shocks versus small shocks (e.g.: Hopenhayn and Rogerson (1993)). In contrast, models without adjustment costs generate smooth relationships between productivity shocks and wages regardless of the size or sign of the shock. To examine this, we divide the η_{jt} distribution into equally sized quintiles for positive and negative shocks. We run our baseline log-linear passthrough regression, interacting η_{jt} with indicators for these quintiles. The resulting coefficients on η_{jt} are plotted on Figure 6. On the right side, indicated by blue squares, we observe that passthrough for small positive shocks is high and decreases as the magnitude of the positive shock increases. Conversely, for negative shocks, firms do not adjust wages (on average) for small magnitudes, as indicated by the imprecise estimates close to zero. Passthrough then increases as the magnitude of the negative shock becomes larger. This suggests that firms face higher separation costs than hiring costs, limiting their ability to reduce labor input when experiencing negative shocks. This asymmetry aligns with our findings in section 5.1, which indicate that adjustment costs lead firms to hoard labor, resulting in higher wages and employment. These results collectively demonstrate the importance of all three mechanisms in driving the degree of passthrough and how it varies across firms.

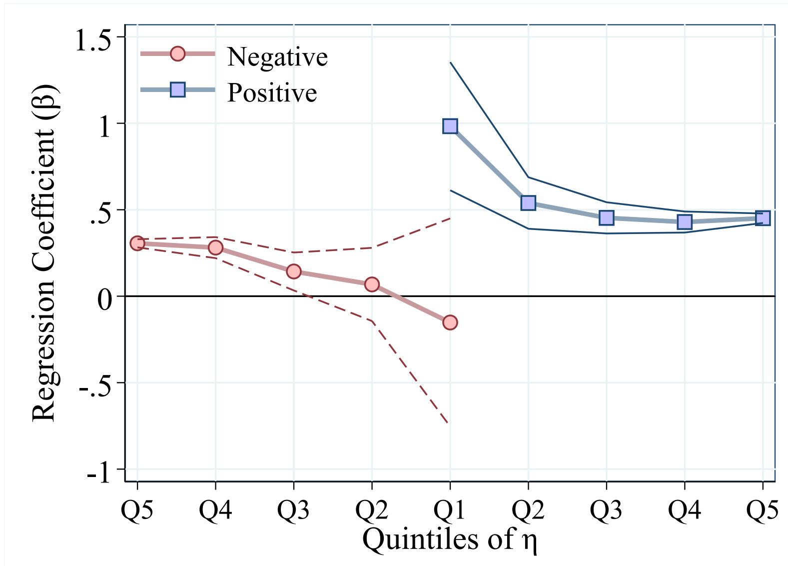
6.2 The Role of Labor Market Imperfections in Passthrough

In this section, we use the structure of the model to measure the relative importance of each passthrough mechanism by constructing counter-factual passthrough elasticity

[63]See Seegmiller (2021) for a discussion of the link between worker tenure and adjustment costs.

[64]For each firm, we define the market churn as the share of all workers within that firm's 4-digit industry who separate from their job (as opposed to staying) in a given year.

Figure 6 – Asymmetric Passthrough from TFP Shocks to Wages



Note: This figure shows the passthrough to firm-level wages for positive and negative shocks. The smooth and dashed lines represent 95% confidence intervals.

distributions under different restrictions on the model.[65]

Case 1: We first consider passthrough in a counter-factual model with atomistic firms, no adjustment costs, and log-linear production and labor supply functions. In Appendix B.3, we show that passthrough in this case is constant. To calculate this constant in our model and data, we set the Cobb-Douglas output elasticities (α_M and α_L) equal to the mean output elasticities for materials and labor from our flexible production function estimation (see Table I). We also choose a fixed labor supply elasticity parameter ε^L_W of 2.7, which corresponds to our estimate of the mean labor supply elasticity in section 5.1. We find a constant passthrough of 1.34 (see Case 1 in Table VII), which is much higher than in the full model and data (the baseline panel in Table VII).

Case 2: Our second counter-factual builds on the first by adding in the full flexible production function estimates from the model.[66] We keep our chosen level of ε^L_W, but now calculate all the other terms in the passthrough expression using the estimated production function. Since markdowns are constant, there is no passthrough to markdowns, but passthrough to the MRPL, and thus to wages, is no longer a constant across firms. We see that allowing for heterogeneous output elasticities and a flexible production func-

[65] We perform a similar theoretical exercise in Appendix B.3.
[66] This corresponds to the third exercise in Appendix B.3.

Table VII – Counterfactual Moments

	Case 1	Case 2		Case 3		
	ε_η^W	ε_η^W		ε_η^W	ε_η^{MRPL}	ε_η^μ
Mean	1.34	2.22		1.21	1.41	-0.20
P50	1.34	1.56		1.22	1.31	-0.06
SD	0.00	1.71		0.17	0.24	0.32
	Case 4			Baseline		
	ε_η^W	ε_η^{MRPL}	ε_η^μ	ε_η^W	ε_η^{MRPL}	ε_η^μ
Mean	1.97	2.29	-0.32	0.36	2.20	-1.84
P50	1.42	1.61	-0.08	0.34	2.13	-1.78
SD	1.59	1.87	0.66	0.18	0.60	0.54

Note: Table VII shows the cross sectional moments of the firm-level elasticities of wages, MRPL, and markdowns with respect to η. Number of observations rounded to the nearest thousand.

tion increases mean passthrough relative to the log-linear case. Average passthrough is much higher than the baseline estimate (2.22 versus 0.36) and also more disperse (standard deviation of 1.71 versus 0.18). This suggests that the presence of market power and adjustment costs act to both significantly reduce the level of passthrough, as well as compress the distribution of passthrough. In this way, the presence of labor market imperfections appears to *reduce* labor income risk by dampening the response of firms to productivity shocks.

Case 3: Our third counter-factual examines the effect of labor market power. Here we return to the Cobb-Douglas case without adjustment costs, but assume that the labor supply curve is generated by a simple logit supply system such that the labor supply elasticity for each firm is equal to $\varepsilon_{\frac{L}{W}jt} = \bar{\varepsilon}_{\frac{L}{W}k}(1 - S_{jt})$, where $\bar{\varepsilon}_{\frac{L}{W}k}$ is a parameter that varies by industry (indexed by k)[67] and S_{jt} is the firm's local labor market employment share.[68] We find that, relative to Case 1, adding a simple labor supply model with endogenous markdowns reduces average passthrough from 1.34 to 1.21. Passthrough to the MRPL goes up relative to Case 1, but that increase is offset by passthrough to markdowns of -0.2. Note that this also demonstrates the degree to which heterogeneity in market power affects not just passthrough to markdowns, but also passthrough to the MRPL through the labor demand elasticity (since there is no other source of passthrough

[67] We choose $\bar{\varepsilon}_{\frac{L}{W}k}$ such that $E[\bar{\varepsilon}_{\frac{L}{W}j}(1 - S_{jt})]$ equals the mean estimated labor supply elasticity for that industry (see Table A.9) given the distribution of market shares in the data.

[68] This case corresponds to a parameterized version of exercise 5 in section B.3. Passthrough to markdowns, MRPL and wages are calculated using equations A.15 and A.16.

heterogeneity here, but we still see significant heterogeneity in passthrough to MRPL). Notably, because passthrough to the MRPL and markdowns are correlated, the resulting dispersion in passthrough to the wage is much lower than dispersion in passthrough to both MRPL and markdowns. We show in Appendix B.3 that in this setting, passthrough to wages is decreasing while passthrough to the MRPL and markdowns are increasing in absolute value, confirming our earlier discussions in sections 5.3 and 6.1.

Case 4: Our fourth counter-factual combines the previous two, allowing for a fully flexible production function with the same simple logit labor supply model. As with Case 3 vs. Case 1, we can see here that the addition of a simple market friction (endogenous labor supply elasticities) reduces passthrough to wages (1.97) relative to the Case 2 (2.22), which has flexible production but no passthrough to markdowns. While passthrough to the MRPL increases in size and dispersion, passthrough to the markdown acts to dampen this increase, reducing dispersion in passthrough to wages relative to Case 2.

Overall, we can see that relative to the constant passthrough of Case 1, the addition of the flexible production technology and labor market power increases passthrough to the MRPL towards the baseline level (mean of 2.2), while also moving passthrough to markdowns towards the baseline average of -1.85. The remaining gap between Case 4 and the baseline case is still quite large (especially with respect to passthrough to markdowns), which suggests that there is a large potential role both for adjustment costs, and for more complex labor supply mechanisms to play in driving observed passthrough.

6.3 Labor Market Imperfections and Income Risk

Our counterfactual results above suggest that the presence of market imperfections such as endogenous labor supply elasticities and adjustment costs reduce labor income volatility relative to a counter-factual world with little market power and no adjustment costs (as in Case 2). To examine this, we construct the predicted distribution of changes in log wages that arises from shocks to persistent productivity in both our baseline estimates (by multiplying each firm's passthrough elasticity $\varepsilon^{W}_{\eta jt}$ by η_{jt}) and our counter-factual settings (multiplying each firm's counter-factual passthrough elasticity by η_{jt}). We denote the dispersion (standard deviation) of these predicted wage changes as $\hat{\Delta}^c_\eta$, where $c \in \{b, 1, 2, 3, 4\}$ indicates whether the change distribution was calculated using the baseline (b) or counter-factual (1 to 4) elasticity distributions. We take $\hat{\Delta}^c_\eta$ as a measure of income volatility arising from firm risk. In a perfectly competitive world with no passthrough to wages, this measure would be zero as wages are not exposed to idiosyncratic firm risk. If passthrough is greater than zero, then this measure will depend on the dispersion of the productivity shock and passthrough distributions and the correlation between the two.

The baseline measure, $\hat{\Delta}_{\eta}^{b}$, calculated using our full passthrough elasticity and η_{jt} distributions is 0.019. This is much lower than the volatility measure calculated under counter-factual case 2 ($\hat{\Delta}_{\eta}^{2}$) which we calculate as 0.083. Since case 2 allows for a fully flexible technological response to productivity shocks, but shuts down adjustment costs and endogenous market power, this implies that labor market imperfections may reduce wage volatility arising from firm risk by over 77%. This income volatility is more than 4 times higher in a setting without frictions (case 2) relative to our estimated baseline. The volatility under counter-factual case 2 is also larger than for case 1, which similarly has no labor market frictions (other than a fixed supply elasticity) but a Cobb-Douglas production function. We find $\hat{\Delta}_{\eta}^{1} = 0.067$, suggesting that allowing for a flexible production function increases income risk via additional dispersion in the MRPL. We also calculate $\hat{\Delta}_{\eta}^{3} = 0.041$ and $\hat{\Delta}_{\eta}^{4} = 0.074$ for cases 3 and 4 respectively. The estimate for case 4 shows that adding even a simple market imperfection such as a basic logit labor supply mechanism significantly reduces worker income exposure to firm risk (a volatility measure of 0.074 versus 0.083).

7 Conclusions

In this paper, we develop a simple yet general dynamic model of the firm. We use this model to illuminate the mechanisms that link firm wages to idiosyncratic changes in firm productivity. While a significant body of literature has highlighted the importance of this link, we are the first to decompose it into effects on a firm's marginal product of labor and firm markdowns. We demonstrate that the direction and magnitude of this relationship depend not only on firm-level market power but also on the shape of the production function and the dynamic labor adjustment costs the firm faces. Constrained firms struggle to pass productivity shocks onto wages, often resulting in them retaining workers and paying wages that exceed the workers' marginal revenue product. This has direct implications for allocative efficiency and labor market policy. We find that both markdowns and the marginal product of labor are highly sensitive to productivity shocks. This sensitivity is largely due to a firm's ability to adjust its flexible inputs, a factor overlooked by frameworks that rely on value-added production functions. Larger firms possess greater market power but are also more constrained by adjustment costs. This combination results in reduced passthrough and income risk for their employees. In fact, we reveal that both endogenous markdowns and adjustment costs significantly mitigate the wage fluctuations experienced by workers.

The framework we develop in this paper is quite general, and can be used as a powerful tool to examine a number of interesting questions. While we endeavor to leave our adjustment cost and labor supply models unspecified, one could easily drop a wide class of such models directly into this framework. This framework could also easily be built into a general equilibrium model, allowing researchers to use our flexible estimation approach to answer broader macroeconomic questions using micro-level data. One key avenue is to extend our framework to allow for market power in outputs. This is feasible in scenarios where we observe firm-level variation in output prices, but becomes challenging when considering the entire private sector, as we do in this paper. Ultimately, our framework can be a robust tool for policy analysis, as it builds upon and generalizes an existing policy-relevant literature which centers on production function and market power estimation.

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Supplemental Online Appendix

FOR ONLINE PUBLICATION

A Two-Way Fixed Effects Model Additional Material

The identification of the parameters on the individual covariates, Γ_t, individual fixed effects α_i and firm time fixed effects $\psi_{j(i,t)t}$ using the two way fixed effect model with time varying firm effects is similar to Chan *et al.* (2022). One issue about the identification is that the model may face limited mobility bias. The richness of our data helps mitigate this issue which is illustrated in Figure A.1 .

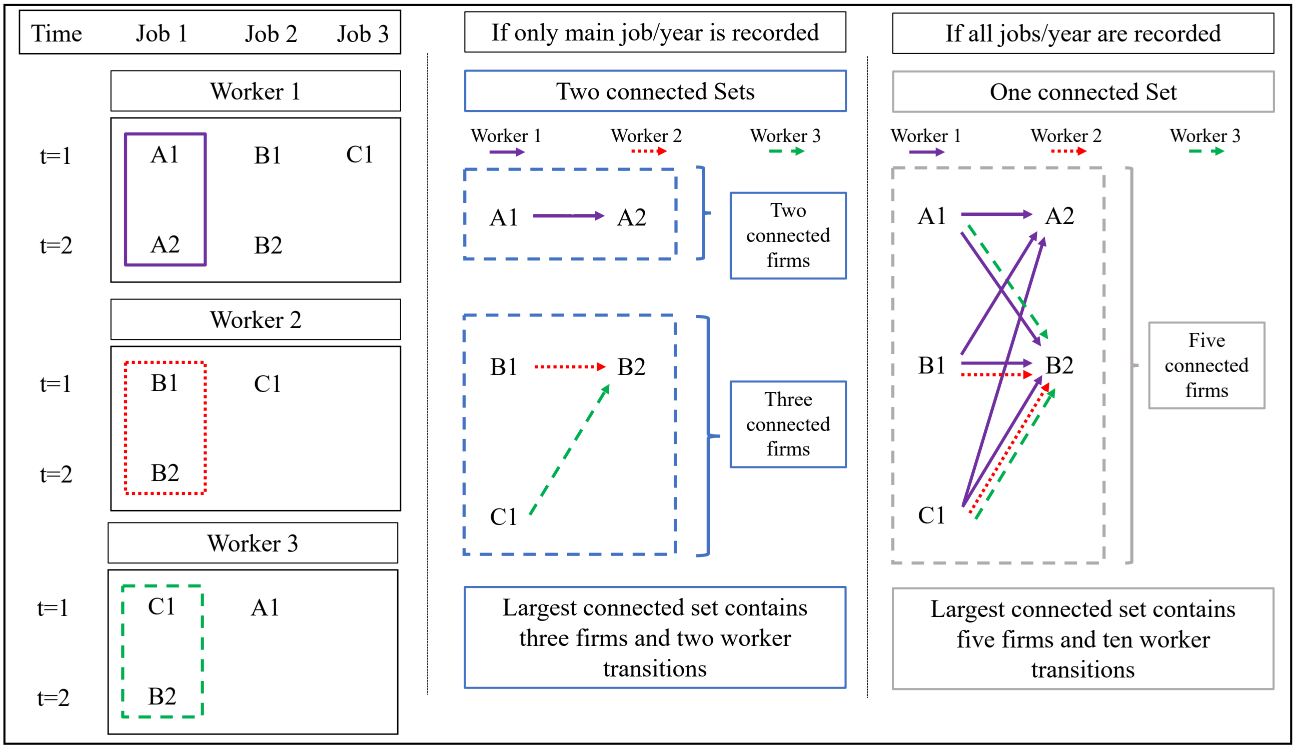
Figure A.1 provides a graphical representation of how we construct the connected set in our model with firm-time fixed effects and multiple observations per worker within a year. The left panel shows a theoretical set of jobs across two years for three different workers. In this example, worker 1 has three jobs in period 1, working at firms A, B, and C. In period 2, worker 1 has only two jobs—working at firms A and B—and so on. Workers' main jobs—those that provide the largest income in a year—are identified by solid purple, dotted red, and dashed green boxes. Because we estimate firm effects separately for each year, we treat each firm-year observation as a separate firm. Thus, A1 and A2 refer to firm A in periods 1 and 2, respectively.

The middle panel shows the network graph of all 5 firm-year nodes if we were to consider only each worker's primary job (as is typically done in the literature). For example, worker 1 moves from A1 in period 1 to A2 in period 2, while worker 3 moves from C1 to B2. The result is two connected sets; the first, with firms A1 and A2, and the second (the largest connected set) with firms B1, B2 and C1. Each firm is connected to the rest of the set with just a single worker transition.

The right panel of Figure A.1 shows the network graph when we consider all of the worker-firm pair information available in a year. In this case, each first-period job worked by an individual is connected to every second-period job worked by that same individual. For example, worker 1 is employed in firms A1, B1, and C1, in period 1, and A2, and B2 in period two, leading to a full set of connections between period 1 and period 2 firms as depicted by the multiple solid lines in the right panel of Figure A.1. This leads to a connected set including all 5 firms in the sample. Moreover, each firm in this larger connected set is connected by at least 3 worker transitions to the rest of the set, strengthening the identification of the firm and worker fixed effects.

The common concern about AKM fixed effect regressions—is that there may be many firm-time pairs that are weakly connected to the largest connected set. For example, in our data set, we find that roughly 5.2% of all firm-time observations have only one transition connecting these firms to the largest connected set, with another 13.3% of firm-time observations having only two connections. As noted by Andrews *et al.* (2008), if firm fixed effects are identified using a small number of workers who move across firms, the AKM estimates may be biased, overstating the role of firms relative to the role of sorting in accounting for the variation in labor earnings. Notice, however, that using multiple job observations for workers helps to reduce the extent of this limited mobility bias: if we include only one job per worker, we find that 7.0% of firm-time observations have only one link (versus 5.2% in our baseline sample), and 20.1% have only two links to the largest connected set (versus 13.3% using workers' top three job connections). Furthermore, the limited mobility bias only affects our inference about the importance of firms and sorting in accounting for wage dispersion (the $\psi_{j(i,t)t}$ component), but not the component of the hourly wages accounted for by worker heterogeneity (as measured by $\alpha_i + X_{it}\Gamma_t$), which

Figure A.1 – Connected Sets using Multiple Jobs



Note: Figure A.1 shows how we identify the parameters of the two-way fixed effect model with firm-year fixed effects and multiple jobs per worker-year.

is crucial for the method we use to estimate firms' TFP. Chan *et al.* (2022) further addressed the limited mobility bias problem by removing firm-time observations with low numbers of connections and they estimate the parameters with various restricted connected data set. Their sensitivity tests shows that the degree of the bias in this two-way fixed effect analysis using the Danish administrative data is very small and not concerning.

As is standard in the literature, we can decompose the variance of the log hourly wages as follows

$$Var\left(w_{ijt}\right) = \underbrace{Var\left(\alpha_i + X_{it}\Gamma_t\right)}_{\text{Worker Component}} + \underbrace{Var\left(\psi_{j(i,t)t}\right)}_{\text{Firm Component}} + \underbrace{2 \times Cov\left(\alpha_i + X_{it}\Gamma_t, \psi_{j(i,t)t}\right)}_{\text{Wage Sorting Component}} + \underbrace{Var\left(\xi_{ijt}\right)}_{\text{Residual}}, \tag{A.1}$$

where the first and second components capture the fraction of the variance of the log hourly wages accounted for by heterogeneity across workers and firms, respectively. The third component accounts for the variation in the log hourly wages that can be attributed to the sorting of high-ability workers—as measured by $\alpha_i + X_{it}\Gamma_t$—employed by high-wage firms—as measured by $\psi_{j(i,t)t}$. The results are shown in Table A.1. We find that around 48% of the variance of the log hourly wages is accounted for by workers' observed and unobservable characteristics and 16% is accounted for by firms' time-varying characteristics. Our estimates also show that sorting accounts for almost none of the total variation in hourly wages.

Table A.1 – Variance Decomposition of Log Hourly Wages Using AKM

	1991-2000	2001-2010	Pooled
Variance of hourly wages $Var\left(w_{ijt}\right)$	0.287	0.315	0.302
Worker heterogeneity $Var\left(\alpha_i + X_{it}\Gamma_t\right)$	0.138	0.155	0.148
Firm heterogeneity $Var\left(\psi_{j(i,t)t}\right)$	0.045	0.052	0.049
Residuals $Var\left(\xi_{ijt}\right)$	0.106	0.110	0.108
Wage sorting $2 \times Cov\left(\alpha_i + X_{it}\Gamma_t, \psi_{j(i,t)t}\right)$	-0.001	-0.003	-0.002
Largest connected set	98.0%	99.0%	99.0%
R^2	62.0%	63.0%	63.0%

Note: Table A.1 shows the decomposition of the variance log hourly wages using the AKM estimates, as in Equation (A.1), for two time intervals and for the pooled sample. The sorting correlation in the pooled sample is $corr\left(\alpha_i, \psi_{j(i,t)t}\right) = -0.003$. The total number of worker/job/year observations in the pooled sample is 57.3 million, with a total of 4.3 million unique workers, 3.0 million unique firm/years, and 0.45 million unique firms.

B Model Details

In this section, we specify the details and various derivation steps of our model.

B.1 Details of the FOCs

Our model is:

$$
\begin{aligned}
V_{jt}(I_{jt}) = \max_{L_{jt}, \tilde{Z}_{jt}, K^I_{jt}, M_{jt}} & E_{\epsilon_{jt}}\left[P^Y_t F(K_{jt}, L_{jt}, M_{jt}) e^{\nu_{jt}} \mid I_{jt}\right] - E_{\epsilon_{jt}}\left[W_{jt} \mid I_{jt}, W^c_{jt}\right] L_{jt} - \Phi_{jt} \\
& - P^I_t K^I_{jt} - P^M_t M_{jt} + \beta E_{\epsilon_{jt}, \eta_{jt+1} P_{t+1}}\left[V_{jt+1}(I_{jt+1}) | I_{jt}\right]
\end{aligned}
$$

s.t.

$$
\begin{aligned}
K_{jt+1} &= (1-\delta)K_{jt} + K^I_{jt} \quad \text{(capital evolution)} \\
L_{jt} &= L_j(W^c_{jt}\mathcal{E}^c, \overline{Z}_{jt}, \tilde{Z}_{jt}) \quad \text{(labor supply)}
\end{aligned}
$$

$$
\Phi_{jt} = \Phi_j(L_{jt}, L_{jt-1}, K_{jt}, \overline{Z}_{jt}, \tilde{Z}_{jt}, \tilde{Z}_{jt-1}) \quad \text{(cost/amenity/management)}
$$

Assume L monotone and continuous in $E\left[W_{jt} \mid I_{jt}, W^c_{jt}\right]$.

$$
\begin{aligned}
\Longrightarrow & E_{\epsilon_{jt}}\left[W_{jt} \mid I_{jt}, W^c_{jt}\right] = L^{-1}_j(L_{jt}, \overline{Z}_{jt}, \tilde{Z}_{jt}) \\
\Longrightarrow & W^c_{jt}\mathcal{E}^c = g_j(L_{jt}, \overline{Z}_{jt}, \tilde{Z}_{jt}) \quad \text{(inverse labor supply)}
\end{aligned}
$$

We need FOCs on $\left\{L_{jt}, M_{jt}, \tilde{Z}_{jt}, K^I_{jt}\right\}$. The information set/state vector is $I_{jt} = \{K_{jt}, L_{jt-1}, M_{jt-1}, W_{jt-1}, \overline{Z}_{jt}, \tilde{Z}_{jt-1}\omega_{jt}, \eta_{jt}, \epsilon_{jt-1}, I_{jt-1}, P_t = \left\{P^Y_t, P^M_t, P^I_t\right\}\}$.

The **first order condition** with respect to L_{it} is

$$
\begin{aligned}
\frac{\partial V_{jt}}{\partial L_{jt}} :& E_{\epsilon_{jt}}\left[P_t^Y F_L(.)e^{\nu_{jt}} \mid I_{jt}\right] - \left\{E_{\epsilon_{jt}}\left[W_{jt} \mid I_{jt}, W_{jt}^c\right] + E_{\epsilon_{jt}}\left[\frac{\partial W_{jt}}{\partial L_{jt}} \mid I_{jt}, W_{jt}^c\right] L_{jt}\right\} - \frac{\partial \Phi_{jt}}{\partial L_{jt}} \\
&+ \beta E_{\epsilon_{jt},\eta_{jt+1}P_{t+1}} \frac{\partial\left[V_{jt+1}(I_{jt+1})|I_{jt}\right]}{\partial L_{jt}} = 0 \\
\frac{\partial V_{jt}}{\partial L_{jt}} :& E_{\epsilon_{jt}}\left[P_t^Y F_L(.)e^{\nu_{jt}} \mid I_{jt}\right] - \left\{g_j(L_{jt}, \overline{Z}_{jt}, \tilde{Z}_{jt}) + \frac{\partial g_j(L_{jt}, \overline{Z}_{jt}, \tilde{Z}_{jt})}{\partial L_{jt}} L_{jt}\right\} - \frac{\partial \Phi_{jt}}{\partial L_{jt}} \\
&+ \beta E_{\epsilon_{jt},\eta_{jt+1}P_{t+1}} \frac{\partial\left[V_{jt+1}(I_{jt+1})|I_{jt}\right]}{\partial L_{jt}} = 0 \\
\frac{\partial V_{jt}}{\partial L_{jt}} :& P_t^Y \frac{\partial F}{\partial L_{jt}} e^{\omega_{jt}} \mathcal{E} = W_{jt}^c \mathcal{E}^c + \frac{\partial g_j(.)}{\partial L_{jt}} L_{jt} + \frac{\partial \Phi_{jt}}{\partial L_{jt}} - \beta E_{\epsilon_{jt},\eta_{jt+1}P_{t+1}} \frac{\partial\left[V_{jt+1}(I_{jt+1})|I_{jt}\right]}{\partial L_{jt}} = 0
\end{aligned}
$$

The **envelope condition** for L_{jt} is

$$
\frac{\partial V_{jt}}{\partial L_{jt-1}} : \frac{V_{jt}(I_{jt})}{\partial L_{jt-1}} = -\frac{\partial \Phi_{jt}}{\partial L_{jt-1}}.
$$

$$
\begin{aligned}
P_t^Y \frac{\partial F}{\partial L_{jt}} e^{\omega_{jt}} \mathcal{E} &= W_{jt}^c \mathcal{E}^c + L_{jt} \frac{\partial g_{jt}}{\partial L_{jt}} + \frac{\partial \Phi_{jt}}{\partial L_{jt}} - \frac{\partial}{\partial L_{jt}} \beta E_{\epsilon_{jt},\eta_{jt+1}p_{t+1}}\left[V_{jt+1}(I_{jt+1})|I_{jt}\right] \\
\underbrace{P_t^Y \frac{\partial F}{\partial L_{jt}} e^{\omega_{jt}} \mathcal{E}}_{\text{Expected MRPL}} - \frac{\partial \Phi_{jt}}{\partial L_{jt}} + \frac{\partial}{\partial L_{jt}} \beta E_{\epsilon_{jt},\eta_{jt+1}p_{t+1}}\left[V_{jt+1}(I_{jt+1})|I_{jt}\right] &= W_{jt}^c \mathcal{E}^c + L_{jt} \frac{\partial g_{jt}}{\partial L_{jt}}
\end{aligned}
$$

$$
\underbrace{P_t^Y \frac{\partial F}{\partial L_{jt}} e^{\omega_{jt}} \mathcal{E}}_{\text{Expected MRPL}} - \frac{\partial \Phi_{jt}}{\partial L_{jt}} + \frac{\partial}{\partial L_{jt}} \beta E_{\epsilon_{jt},\eta_{jt+1}p_{t+1}}\left[V_{jt+1}(I_{jt+1})|I_{jt}\right] = W_{jt}^c \mathcal{E}^c \left(1 + \frac{L_{jt}}{g_{jt}(.)} \frac{\partial g_{jt}}{\partial L_{jt}}\right)
$$

$$
\implies W_{jt}^c \mathcal{E}^c = \frac{\varepsilon_{\frac{L}{W}jt}}{1 + \varepsilon_{\frac{L}{W}jt}} E_{\epsilon_{jt}}\left[MRPL_{jt}\right] - \frac{\partial \Phi}{\partial L_{jt}} + \frac{\partial}{\partial L_{jt}} \beta E_{\epsilon_{jt},\eta_{jt+1}P_{t+1}}\left[V_{jt+1}(I_{jt+1})|I_{jt}\right])
$$

This gives us our Equation 6 in the paper.

The order condition with respect to $\tilde{Z}_{jt}$ is

$$\frac{\partial V_{jt}}{\partial \tilde{Z}_{jt}} : E_{\epsilon_{jt}}\left[P_t^Y F_L(.)e^{\nu_{jt}} \mid I_{jt}\right]\frac{\partial L_{jt}}{\partial \tilde{Z}_{jt}} - \left\{E_{\epsilon_{jt}}\left[W_{jt} \mid I_{jt}, W_{jt}^c\right] + E_{\epsilon_{jt}}\left[\frac{\partial W_{jt}}{\partial L_{jt}} \mid I_{jt}, W_{jt}^c\right] L_{jt}\right\}\frac{\partial L_{jt}}{\partial \tilde{Z}_{jt}}$$
$$- \frac{E_{\epsilon_{jt}}\left[W_{jt} \mid I_{jt}, W_{jt}^c\right]}{\partial \tilde{Z}_{jt}} L_{jt} - \left\{\frac{\partial \Phi_{jt}}{\partial L_{jt}}\frac{\partial L_{jt}}{\partial \tilde{Z}_{jt}} + \frac{\partial \Phi_{jt}}{\partial \tilde{Z}_{jt}}\right\}$$
$$+ \beta E_{\epsilon_{jt},\eta_{jt+1}P_{t+1}} \frac{\partial\left[V_{jt+1}(I_{jt+1})|I_{jt}\right]}{\partial L_{jt}}\frac{\partial L_{jt}}{\partial \tilde{Z}_{jt}} + \frac{\partial\left[V_{jt+1}(I_{jt+1})|I_{jt}\right]}{\partial \tilde{Z}_{jt}} = 0,$$

but the cross terms can be aggregated to get

$$\frac{\partial V_{jt}}{\partial \tilde{Z}_{jt}} : \left\{E_{\epsilon_{jt}}\left[P_t^Y F_L(.)e^{\nu_{jt}} \mid I_{jt}\right] - \left\{E_{\epsilon_{jt}}\left[W_{jt} \mid I_{jt}, W_{jt}^c\right] + E_{\epsilon_{jt}}\left[\frac{\partial W_{jt}}{\partial L_{jt}} \mid I_{jt}, W_{jt}^c\right] L_{jt}\right\} - \frac{\partial \Phi_{jt}}{\partial L_{jt}}\right.$$
$$\left. + \beta E_{\epsilon_{jt},\eta_{jt+1}P_{t+1}} \frac{\partial\left[V_{jt+1}(I_{jt+1})|I_{jt}\right]}{\partial L_{jt}}\right\}\frac{\partial L_{jt}}{\partial \tilde{Z}_{jt}}$$
$$- \frac{E_{\epsilon_{jt}}\left[W_{jt} \mid I_{jt}, W_{jt}^c\right]}{\partial \tilde{Z}_{jt}} L_{jt} - \frac{\partial \Phi_{jt}}{\partial \tilde{Z}_{jt}} + \frac{\partial\left[V_{jt+1}(I_{jt+1})|I_{jt}\right]}{\partial \tilde{Z}_{jt}} = 0,$$

the first term is equal to zero at the optimum b/c of foc of labor, so we have

$$\frac{\partial V_{jt}}{\partial \tilde{Z}_{jt}} : -\frac{E_{\epsilon_{jt}}\left[W_{jt} \mid I_{jt}, W_{jt}^c\right]}{\partial \tilde{Z}_{jt}} L_{jt} - \frac{\partial \Phi_{jt}}{\partial \tilde{Z}_{jt}} + \frac{\partial\left[V_{jt+1}(I_{jt+1})|I_{jt}\right]}{\partial \tilde{Z}_{jt}} = 0,$$

which is what we have above.

The **first order condition** with respect to K_{jt}^I is

$$\frac{\partial V_{jt}}{\partial K_{jt}^I} : -P_t^I + \beta E_{\epsilon_{jt},\eta_{jt+1}P_{t+1}} \frac{\partial\left[V_{jt+1}(I_{jt+1})|I_{jt}\right]}{\partial K_{jt+1}}\frac{\partial K_{jt+1}}{\partial K_{jt}^I} = 0,$$

and the **envelope condition** on K_{jt} is

$$\frac{\partial V_{jt}}{\partial K_{jt}} : \frac{\partial V_{jt}}{\partial K_{jt}} = E_{\epsilon_{jt}}\left[P_t^Y F_K(.)e^{\nu_{jt}} \mid I_{jt}\right] + P_t^I(1-\delta) + \beta E_{\epsilon_{jt},\eta_{jt+1}P_{t+1}}\left[\frac{V_{jt+1}(I_{jt+1})}{K_{jt+1}}|I_{jt}\right]\frac{\partial K_{jt+1}}{\partial K_{jt}}.$$

Note, we can expand the envelope condition to account for the dependencies of L and M on

K_{jt}, that is

$$\frac{\partial V_{jt}}{\partial K_{jt}}:\frac{\partial V_{jt}}{\partial K_{jt}}=E_{\epsilon_{jt}}\left[P_t^Y F_K(.)e^{\nu_{jt}}\mid I_{jt}\right]+E_{\epsilon_{jt}}\left[P_t^Y F_L(.)e^{\nu_{jt}}\mid I_{jt}\right]\frac{\partial L_{jt}}{\partial K_{jt}}+E_{\epsilon_{jt}}\left[P_t^Y F_M(.)e^{\nu_{jt}}\mid I_{jt}\right]\frac{\partial M_{jt}}{\partial K_{jt}}+$$
$$-\left\{\left\{E_{\epsilon_{jt}}\left[W_{jt}\mid I_{jt},W_{jt}^c\right]+E_{\epsilon_{jt}}\left[\frac{\partial W_{jt}}{\partial L_{jt}}\mid I_{jt},W_{jt}^c\right]L_{jt}\right\}-\frac{\partial \Phi_{jt}}{\partial L_{jt}}\right\}\frac{\partial L_{jt}}{\partial K_{jt}}+$$
$$P_t^I(1-\delta)+\beta E_{\epsilon_{jt},\eta_{jt+1}P_{t+1}}\left[\frac{V_{jt+1}(I_{jt+1})}{K_{jt+1}}|I_{jt}\right]\frac{\partial K_{jt+1}}{\partial K_{jt}}.$$

but all the cross terms are 0 at the solution, i.e.: $\frac{\partial M_{jt}^*}{\partial K_{jt}}=0$ otherwise, we will not be at the max.

The **first order condition** with respect to M_{jt} is

$$\frac{\partial V_{jt}}{\partial M_{jt}}:E_{\epsilon_{jt}}\left[P_t^Y F_M(.)e^{\nu_{jt}}\mid I_{jt}\right]-P_t^M+\beta E_{\epsilon_{jt},\eta_{jt+1}P_{t+1}}\frac{\partial\left[V_{jt+1}(I_{jt+1})|I_{jt}\right]}{\partial M_{jt}}=0,$$

and the **envelope condition** is

$$\frac{\partial V_{jt}}{\partial M_{jt-1}}:\frac{\partial V_{jt}}{\partial M_{jt-1}}=0.$$

In summary, we have that

L_{jt}:

$$W_{jt}^c\mathcal{E}^c=\frac{\varepsilon_{W_{jt}}^L}{1+\varepsilon_{W_{jt}}^L}E_{\epsilon_{jt}}\left[MRPL_{jt}\right]-\frac{\partial\Phi}{\partial L_{jt}}+\frac{\partial}{\partial L_{jt}}\beta E_{\epsilon_{jt},\eta_{jt+1}P_{t+1}}\left[V_{jt+1}(I_{jt+1})|I_{jt}\right])$$

$\tilde{Z}_{jt}$:

$$0=L_{jt}\frac{\partial g_{jt}}{\partial\tilde{Z}_{jt}}+\frac{\partial\Phi_{jt}}{\partial\tilde{Z}_{jt}}-\frac{\partial}{\partial\tilde{Z}_{jt}}\beta E_{\epsilon_{jt},\eta_{jt+1}P_{t+1}}\left[V_{jt+1}(I_{jt+1})|I_{jt}\right]$$

M_{jt}:

$$P_t^Y\frac{\partial F(.)}{\partial M_{jt}}e^{\omega_{jt}}\mathcal{E}=P_t^M$$

K_{jt}^I:

$$\beta\frac{\partial E_{\epsilon_{jt},\eta_{jt+1}P_{t+1}}\left[V_{jt+1}(I_{jt+1})|I_{jt}\right]}{\partial K_{jt+1}}=P_t^I$$

B.2 Passthrough Decomposition Details

Firms' wage setting and therefore passthrough from TFP to wages depends on three factors: production technology, market power and adjustment costs. In this section, we study the firms' wage setting problem when one or two or all of these factors are absent from the model. Through a series of these exercises, we discuss how each of these factors contribute to the passthrough elasticity from TFP to wages.

Taking logs on both side of the first order condition with respect to labor, and taking the total derivative with respect to the persistent shocks, we get:[69]

$$\begin{aligned}\frac{\mathrm{d}w_{jt}}{\mathrm{d}\eta_{jt}} &= \frac{\mathrm{d}\mu_{jt}}{\mathrm{d}\eta_{jt}} + \frac{\mathrm{d}mrpl_{jt}}{\mathrm{d}\eta_{jt}} \\ &= \frac{\mathrm{d}\mu_{jt}}{\mathrm{d}\eta_{jt}} + \frac{\mathrm{d}f^l_{jt}}{\mathrm{d}\eta_{jt}} + 1 \\ &= \frac{\mathrm{d}\mu_{jt}}{\mathrm{d}\eta_{jt}} + \frac{\partial f^l_{jt}}{\partial l_{jt}}\frac{\mathrm{d}l_{jt}}{\mathrm{d}\eta_{jt}} + \frac{\partial f^l_{jt}}{\partial m}\frac{\mathrm{d}m_{jt}}{\mathrm{d}\eta_{jt}} + 1 \end{aligned} \tag{A.2}$$

Where $f^l_{jt} = \log \frac{F_{jt}}{L_{jt}} = \log F^L_{jt}$. The second equation comes from taking logs and derivatives with respect to η on both side of the following equation:

$$MRPL_{jt} = P^Y_t F^L_{jt} \exp(\mathbb{E}(\omega_{jt}|\omega_{jt-1}) + \eta_{jt} + \varepsilon_{jt})$$

Similarly we take logs on both side of the first order condition with respect to material (equation 5), and we then take derivative with respect to persistent shocks and we get the following:

$$\begin{aligned} &\frac{\mathrm{d}\log(P^Y_t F^M_{jt} \exp \mathbb{E}(\omega_{jt}|\omega_{jt-1}) + \eta_{jt} + \varepsilon_{jt}\mathcal{E})}{\mathrm{d}\eta_{jt}} = \frac{\mathrm{d}\log P^M_t}{\mathrm{d}\eta_{jt}} \\ \Longrightarrow\ & \frac{\mathrm{d}f^M_{jt}}{\mathrm{d}\eta_{jt}} + 1 = 0 \\ \Longrightarrow\ & \frac{\partial f^m_{jt}}{\partial l_{jt}}\frac{\mathrm{d}l_{jt}}{\mathrm{d}\eta_{jt}} + \frac{\partial f^m_{jt}}{\partial m}\frac{\mathrm{d}m_{jt}}{\mathrm{d}\eta_{jt}} = -1 \end{aligned} \tag{A.3}$$

Where $f^m_{jt} = \log \frac{F_{jt}}{M_{jt}} = \log F^M_{jt}$. From the equation above we get that

$$\frac{\mathrm{d}m_{jt}}{\mathrm{d}\eta_{jt}} = \frac{-1 - \frac{\partial f^m_{jt}}{\partial l_{jt}}\frac{\mathrm{d}l_{jt}}{\mathrm{d}\eta_{jt}}}{\frac{\partial f^m_{jt}}{\partial m_{jt}}} = -\frac{1}{f_{mm}} - \frac{f_{ml}}{f_{mm}}\frac{\mathrm{d}l}{\mathrm{d}\eta} \tag{A.4}$$

Where $f_{mm} = \frac{\partial f^m_{jt}}{\partial m_{jt}}$.[70] Note that in the last equation we saved the subscripts jt for the ease of notation.

Furthermore from the labor supply function we can write the invert labor supply function as: $\overline{W}_{jt} = g(L_{jt})$[71]. Taking logs on both side of the inverse labor supply function, then take

[69] Note that all lower case letters denote the log of the variables. For example, $w_{jt} = \log W_{jt}$

[70] Similarly, we have $f_{mml} = \frac{\partial f^m_{jt}}{\partial l_{jt}}$, $f_{lm} = \frac{\partial f^l_{jt}}{\partial m_{jt}}$, and $f_{ll} = \frac{\partial f^l_{jt}}{\partial l_{jt}}$

[71] Without lost of generality, we leave out the terms $\overline{Z}_{jt}$ for simplicity. The theoretical arguments in these decomposition exercises remain unchanged if $\overline{Z}_{jt}$ are included.

derivatives with respect to η_{jt} on both sides, we get that

$$\frac{\mathrm{d}\log \overline{W}_{jt}}{\mathrm{d}\eta_{jt}} = \frac{\mathrm{d}w_{jt}}{\mathrm{d}\eta_{jt}} = \frac{\mathrm{d}\log g(L_{jt})}{\mathrm{d}\eta_{jt}} = \frac{\mathrm{d}\log g(L_{jt})}{\mathrm{d}l_{jt}}\frac{\mathrm{d}l_{jt}}{\mathrm{d}\eta_{jt}} = \frac{1}{\varepsilon^L_{Wjt}}\frac{\mathrm{d}l_{jt}}{\mathrm{d}\eta_{jt}} \tag{A.5}$$

Where ε^L_{Wjt} denotes the labor supply elasticity firm faces. We can plug equation A.4 and A.5 back into equation A.2 and solve for $\frac{\mathrm{d}l_{jt}}{\mathrm{d}\eta_{jt}}$ and get:

$$\frac{\mathrm{d}l}{\mathrm{d}\eta} = \frac{-\frac{\mathrm{d}\mu}{\mathrm{d}\eta} + \frac{f_{lm}}{f_{mm}} - 1}{f_{ll} - \frac{f_{lm}f_{ml}}{f_{mm}} - \frac{1}{\varepsilon^L_W}} \tag{A.6}$$

Note that all terms in the above equation are indexed by subscript jt. We can then derive $\frac{\mathrm{d}m_{jt}}{\mathrm{d}\eta_{jt}}$ from equation A.4. We now can plug $\frac{\mathrm{d}l}{\mathrm{d}\eta}$ and $\frac{\mathrm{d}m}{\mathrm{d}\eta}$ back in to the passthrough equation 8 so the passthrough to MRPL can be re-written as:

$$\begin{aligned}\frac{\mathrm{d}mrpl}{\mathrm{d}\eta} =& (f_{ll} - \frac{f_{lm}f_{ml}}{f_{mm}})\Big(\frac{\frac{f_{lm}}{f_{mm}} - 1 - \frac{\mathrm{d}\mu}{\mathrm{d}\eta}}{f_{ll} - \frac{f_{lm}f_{ml}}{f_{mm}} - \frac{1}{\varepsilon^L_W}}\Big) - \frac{f_{lm}}{f_{mm}} + 1 \\ =& (1-\zeta)(1 - \frac{f_{lm}}{f_{mm}}) - \zeta\frac{\mathrm{d}\mu}{\mathrm{d}\eta}\end{aligned} \tag{A.7}$$

Where $\zeta = \frac{f_{ll} - \frac{f_{lm}f_{ml}}{f_{mm}}}{f_{ll} - \frac{f_{lm}f_{ml}}{f_{mm}} - \frac{1}{\varepsilon^L_W}}$. The passthrough to wages is then

$$\frac{\mathrm{d}w}{\mathrm{d}\eta} = (1-\zeta)\Big(1 - \frac{f_{lm}}{f_{mm}} + \frac{\mathrm{d}\mu}{\mathrm{d}\eta}\Big) \tag{A.8}$$

Suppose the production function F takes a Cobb-Douglas form:

$$F(K,L,M) = K^{\alpha_K}L^{\alpha_L}M^{\alpha_M}$$

Then we have $\log(F_L)$ and $\log(F_M)$ as

$$\begin{aligned}\log(F_L) =& \log(\alpha_L K^{\alpha_K}L^{\alpha_L - 1}M^{\alpha_M}) = \alpha_L + \alpha_K k + (\alpha_L - 1)\ell + \alpha_M m \\ \log(F_M) =& \log(\alpha_M K^{\alpha_K}L^{\alpha_L - 1}M^{\alpha_M}) = \alpha_L + \alpha_K k + \alpha_L \ell + (\alpha_M - 1)m\end{aligned}$$

so ζ can be simplified as $\zeta = \frac{1-\alpha_m-\alpha_l}{1-\alpha_m-\alpha_l+(1-\alpha_m)\frac{1}{\varepsilon^L_{Wjt}}}$

We next decompose the passthrough to the markdown component.

$$\frac{d\log\mu}{d\eta} = \frac{d\log\mu^{\varepsilon}}{d\eta} + \frac{d\log\mu^{\phi}}{d\eta}$$

Where

$$\frac{d\log\mu^{\varepsilon}}{d\eta} = \frac{1}{\varepsilon_W^L(1+\varepsilon_W^L)}\frac{d\varepsilon_W^L}{d\eta} \tag{A.9}$$

$$\begin{aligned}\frac{d\log\mu^{\phi}}{d\eta} &= \frac{d\log\left(1-\frac{\frac{\partial\phi}{\partial L}-\frac{\partial\overline{V}}{\partial L}}{\overline{MRPL}}\right)}{d\eta}\\ &= -\frac{1}{1-\frac{\frac{\partial\phi}{\partial L}-\frac{\partial\overline{V}}{\partial L}}{\overline{MRPL}}}\frac{\overline{MRPL}\frac{d(\frac{\partial\phi}{\partial L}-\frac{\partial\overline{V}}{\partial L})}{d\eta}-(\frac{\partial\phi}{\partial L}-\frac{\partial\overline{V}}{\partial L})\frac{d\overline{MRPL}}{d\eta}}{\overline{MRPL}^2}\end{aligned} \tag{A.10}$$

B.3 Model Mechanisms and Sources of Passthrough

To understand how technology, market power and adjustment costs affect the wage passthrough elasticity, we examine equations 9, A.7 and A.8 when one, two, or all three factors are absent from the model. We organize these into five exercises and derive some predictions related to the passthrough mechanisms in each case. We test these predictions in the data and estimated model in the main body of the paper (sections 5 and 6).

First exercise: Consider a version of our model where labor markets are perfectly competitive, and adjustment costs and labor market power are absent. In this case, the labor supply elasticity $\varepsilon_W^L = \infty$ and thus $\zeta = 1$, which implies (from equation A.8) that $\frac{\mathrm{d}w}{\mathrm{d}\eta} = 0$, independently of the production technology. The intuition is that in perfectly competitive labor markets, firms are price takers and adjust inputs in respond to idiosyncratic shocks such that their marginal productivity of labor equals the market wage. Hence, firms do not pass any persistent idiosyncratic firm-level shocks to wages.

Second exercise: Suppose that firms in our model face a simple form of monopsonistic competition in labor markets (as in Lamadon *et al.* (2022) and Kroft *et al.* (2020), and Card *et al.* (2018)). To isolate the role of this market imperfection, we assume that firms do not face adjustment costs, firms operate with a simple Cobb-Douglas production technology: $Y_{jt} = K_{jt}^{\alpha_K}L_{jt}^{\alpha_L}M_{jt}^{\alpha_M}e^{\nu_{jt}}$ (implying constant output elasticities and homogeneous returns to scale), and firms are atomistic and face a log-linear labor supply curve. This means the labor supply elasticity is a fixed homogeneous parameter regardless of firm size or market share ($\varepsilon_{Wjt}^L = \varepsilon_W^L$). In this case passthrough to the markdown equals zero, since the labor supply elasticity is a constant. The wage passthrough elasticity then equals the MRPL passthrough elasticity and can be written as:

$$\frac{\mathrm{d}w}{\mathrm{d}\eta} = \frac{\mathrm{d}mrpl}{\mathrm{d}\eta} = \frac{\frac{1}{\varepsilon_W^L}}{1-\alpha_M-\alpha_L+(1-\alpha_M)\frac{1}{\varepsilon_W^L}}. \tag{A.11}$$

Since all the terms are constant across firms, so is the passthrough elasticity. Notice also that the passthrough increases with the output elasticities (α_M and α_L) and thus overall returns to scale, and it decreases with the labor supply elasticity.

Third exercise: Following the previous exercise, we now allow firms to have the flexible production function technology from our full model as opposed to Cobb-Douglas. In this case, passthrough to the markdown is still zero since the labor supply elasticity is constant and there are no adjustment costs. However, passthrough to the MRPL (and wages) is no longer a constant. Specifically, we have

$$\frac{\mathrm{d}w}{\mathrm{d}\eta} = \frac{\mathrm{d}mrpl}{\mathrm{d}\eta} = (1-\zeta)(1-\frac{f_{lm}}{f_{mm}}) = \frac{(f_{lm}-f_{mm})\frac{1}{\varepsilon_W^L}}{f_{ll}f_{mm}-f_{lm}f_{ml}-f_{mm}\frac{1}{\varepsilon_W^L}}. \tag{A.12}$$

Note that all terms in the equation above except the labor supply elasticity are indexed by subscript jt. In this case, passthrough to the MRPL and wages can be heterogeneous due to differences in the production technology across firms. Passthrough is declining in the labor supply elasticity parameter (ε_W^L) as before but it is unclear how passthrough elasticities differ across firms due to input levels. Intuitively, if larger firms have higher returns to scale (as we show is the case in section 5.1), they will adjust inputs more in response to productivity shocks. Without adjustment costs or endogenous labor supply elasticities, this will likely translate into higher passthrough elasticities for larger firms. We cannot determine if this is the case without knowing the production function, but we will test this prediction in section 5 after the model is estimated.[72]

Fourth exercise: In the first three exercises, we simplified the model elements such that the passthrough to markdowns equals zero. In the fourth exercise we examine the case when firms are still atomistic and face a log-linear labor supply curve but now must pay adjustment and employment costs with respect to the labor input (i.e.: $\Phi_{jt} \neq 0$). We again assume firms operate with a Cobb-Douglas technology so there is no heterogeneity in returns to scale or output elasticities. In this case passthrough to the markdown is simply $\frac{\mathrm{d}\log\mu_{jt}}{\mathrm{d}\eta_{jt}} = \frac{\mathrm{d}\log\mu_{jt}^{\Phi}}{\mathrm{d}\eta_{jt}}$, and the passthrough to the MRPL can be written as

$$\frac{\mathrm{d}mrpl_{jt}}{\mathrm{d}\eta_{jt}} = \frac{\frac{1}{\varepsilon_W^L}}{1-\alpha_M-\alpha_L+(1-\alpha_M)\frac{1}{\varepsilon_W^L}} - \frac{1-\alpha_M-\alpha_L+(1-\alpha_M)\frac{1}{\varepsilon_W^L}}{1-\alpha_M-\alpha_L}\frac{\mathrm{d}\log\mu_{jt}^{\Phi}}{\mathrm{d}\eta_{jt}}, \tag{A.13}$$

and passthrough to the wage can be written as

$$\frac{\mathrm{d}w_{jt}}{\mathrm{d}\eta_{jt}} = \frac{\frac{1}{\varepsilon_W^L}}{1-\alpha_M-\alpha_L+(1-\alpha_M)\frac{1}{\varepsilon_W^L}} + \frac{(1-\alpha_M)\frac{1}{\varepsilon_W^L}}{1-\alpha_M-\alpha_L}\frac{\mathrm{d}\log\mu_{jt}^{\Phi}}{\mathrm{d}\eta_{jt}}. \tag{A.14}$$

Without (endogenous) labor market power and heterogeneity in output elasticities across firms, the model predicts that the passthrough to markdowns and the passthrough to the MRPL are negatively correlated, while passthrough to markdowns and passthrough to wages are positively correlated (the coefficients on the passthrough to markdowns terms in equation A.13 and A.14 are both constants, and are negative and positive respectively.).[73] This implies that if passthrough to wages is declining in firm characteristics such as firm size, then we should

[72] Note that the labor supply elasticity in this simple exercise is a constant. Once the production functions are estimated the counterfactual passthrough elasticities in equation A.12 can be fully estimated given certain a value of the labor supply elasticity. We estimate the labor supply elasticity in section 5.1 and examine the counterfactual passthrough properties in section 6.2.

[73] As noted above, passthrough to markdowns will be negative if $\frac{\mathrm{d}}{\mathrm{d}\eta_{jt}}\left(\frac{\partial\Phi_{jt}}{\partial L_{jt}} - \frac{\partial}{\partial L_{jt}}\overline{V}_{jt+1}\right) >$

see that passthrough to the MRPL is increasing with firm size, and passthrough to markdowns is increasing in absolute value with size. In section 5, we test and see if these predicted patterns hold in the data.

Fifth exercise: Lastly, we explore the case when firms are not atomistic and the labor supply elasticity is an endogenous function of firm size (as in Berger *et al.* (2022) and Chan *et al.* (2021)). We isolate this mechanism by again assuming firms operate with a Cobb-Douglas technology without adjustment costs. Passthrough to markdowns in this case is $\frac{\mathrm{d}\log\mu_{jt}}{\mathrm{d}\eta_{jt}} = \frac{\mathrm{d}\log\mu^{\varepsilon}_{jt}}{\mathrm{d}\eta_{jt}}$. Similar to previous exercises, we have that the passthrough to the MRPL and wages are given by

$$\frac{\mathrm{d}mrpl_{jt}}{\mathrm{d}\eta_{jt}} = \frac{\frac{1}{\varepsilon^{L}_{Wjt}}}{1-\alpha_M-\alpha_L+(1-\alpha_M)\frac{1}{\varepsilon^{L}_{Wjt}}} - \frac{(1-\alpha_M-\alpha_L)\frac{\mathrm{d}\log\mu^{\varepsilon}_{jt}}{\mathrm{d}\eta_{jt}}}{1-\alpha_M-\alpha_L+(1-\alpha_M)\frac{1}{\varepsilon^{L}_{Wjt}}}, \tag{A.15}$$

$$\frac{\mathrm{d}w_{jt}}{\mathrm{d}\eta_{jt}} = \frac{\frac{1}{\varepsilon^{L}_{Wjt}}}{1-\alpha_M-\alpha_L+(1-\alpha_M)\frac{1}{\varepsilon^{L}_{Wjt}}} + \frac{(1-\alpha_M)\frac{1}{\varepsilon^{L}_{Wjt}}}{1-\alpha_M-\alpha_L+(1-\alpha_M)\frac{1}{\varepsilon^{L}_{Wjt}}}\frac{\mathrm{d}\log\mu^{\epsilon}_{jt}}{\mathrm{d}\eta_{jt}}. \tag{A.16}$$

If labor supply elasticities are decreasing in firm size (or market share), then the passthrough to markdowns will be negative ($\frac{\mathrm{d}\log\mu^{\epsilon}_{jt}}{\mathrm{d}\eta_{jt}} < 0$). Without further assumptions, there are two possible cases. First, if passthrough to wages decreases in size, then passthrough to MRPL will increase in size and passthrough to markdowns will decrease in size (increase in absolute value with size). Second, if passthrough to wages increases in size, it is ambiguous whether passthrough to MRPL and markdowns increase or decrease in size. Additional assumptions on the labor supply function can generate tighter predictions.

We evaluate this exercise in counter-factual 3 (see section 6.2), where we calibrate version of our model with a Cobb-Douglas production function, no adjustment costs, and a simple logit model of labor supply with oligopsonistic competition between firms in the labor market. Figure A.2 shows that in this setting, the relationship between passthrough and firm size corresponds to the first case above. Panel (a) shows that passthrough declines in firm size when the only mechanism at work is a simple oligopsonistic model of labor supply and competition. Similarly, as predicted, in the model with only endogenous market power, passthrough to the MRPL and markdowns are both increasing in size (and market share).

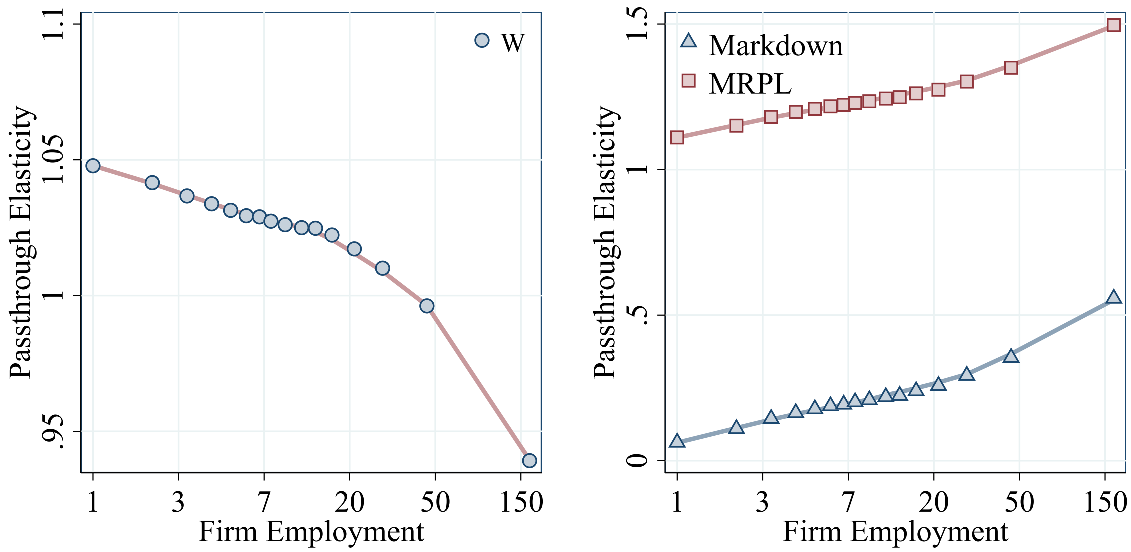
B.4 Ex-post Wage Adjustment Function Estimation

To construct our markdown term free of the ex-post shock in section 5.1, we estimate the ex-post wage adjustment function $f^c(\epsilon_{jt})$ non-parametrically using a complete polynomial series. Specifically we directly estimate the firm level wages w_{jt} as a second degree polynomial function of the transitory shock ϵ_{jt}. Since the transitory shocks are not correlated with the firm's information set in period t, this is equivalent to estimating the residualized wages (the part that does not depend on firms input choices and persistent TFP, i.e. $f^c(\epsilon_{jt})$) on a polynomial of transitory shocks. Table A.2 shows the estimation results. The first column shows the coefficient

$\frac{\left(\frac{\partial\Phi_{jt}}{\partial L_{jt}} - \frac{\partial}{\partial L_{jt}}\overline{V}_{jt+1}\right)}{\overline{MRPL}_{jt}}\frac{\mathrm{d}\overline{MRPL}_{jt}}{\mathrm{d}\eta_{jt}}$.

Figure A.2 – Counterfactual Passthrough by Firm Size

(a) Wages (b) Markdowns and $MRPL$



Note: This figure shows the passthrough to firm-level markdowns, MRPL, and wages in counter-factual case 3, where firms have Cobb-Douglas production functions with no adjustment costs, and face a simple logit labor supply system with oligopsonistic competition between firms in the labor market.

Table A.2 – Estimation of Function $f^c(\epsilon_{jt})$

Coef (ϵ_{jt})	Coef (ϵ_{jt}^2)	Mean of $f^c(\epsilon_{jt})$ (i.e. $\mathcal{E}^c$)	Std. Dev. of $f^c(\epsilon_{jt})$
0.396	-0.323	0.990	0.109

on ϵ_{jt} and the second column shows the coefficient on ϵ_{jt}^2. The estimates shows that f^c is increasing and concave in all ϵ_{jt} in the support (The rounded up 99th percentile of $\epsilon_{jt} = 0.57$ as shown in Table I). On column 3 and 4, we show the mean and standard deviation of $f^c(\epsilon_{jt})$. We try several other specifications for f^c, including more flexible polynomials and specifications with interactions for positive and negative shocks. The results remain largely unaffected.

B.5 Labor Supply Elasticity Estimation

In models without adjustment costs and ex-post wage adjustment, labor supply elasticities can simply be recovered from $\mu_{jt} = \frac{\varepsilon^L_{Wjt}}{1+\varepsilon^L_{Wjt}}$. Given our estimated markdowns, the implied average labor supply elasticity would be 4.3. With adjustment costs and ex-post wage adjustment, the markdown is given by equation 7 so we can not recover ε^L_{Wjt} directly from μ_{jt}. Instead, we leverage the structure and timing assumptions of our model to directly estimate how the quantity of labor responds to wages using a natural set of demand shifters as instruments.

Specifically we estimate the following model equation:

$$L_{jt} = L(\overline{W}_{jt}, \overline{Z}_{jt}) \tag{A.17}$$

Similar to our passthrough estimates, we estimate equation A.17 in two ways. First we use a log-linear form to approximate the supply function, where we regress the firm's labor input in logs ℓ_{jt} on logs of the ability price w_{jt}, components of $\overline{Z}_{jt}$ as above, and a set of time indicators. We do this both using OLS and 2SLS. Our instruments are exogenous variables which shift firm-level demand for labor – namely η_{jt} and ω_{jt-1}. The implicit assumption is that the demand shifters (in this case, idiosyncratic persistent productivity shocks and lagged levels) are not correlated with unobserved supply shifters, and therefor shift the demand curve alone – allowing us to trace out the supply curve with observed changes in wages and labor inputs. This gives us a single estimate of the average labor supply elasticity for our firms. Our second approach is to approximate the supply curve with a complete second-degree polynomial in (log) wages and $\overline{Z}_{jt}$. We also do this using OLS and an IV approach. For the latter, we first predict each endogenous term in the polynomial supply curve (levels, squares, and interaction terms involving w_{jt}) using a complete second degree polynomial in the demand shifters $\{\eta_{jt}, \omega_{jt-1}\}$ and $\overline{Z}_{jt}$, then estimate the supply curve with the predicted polynomial terms. This gives us a distribution of labor supply elasticities, just as in our estimates of the passthrough elasticity.

The results are shown in Table A.3.[74] Columns 1 and 2 show the results from the log-linear approximation. Without instrumenting for wages (using OLS), we find a labor supply elasticity parameter of 0.053. Once we use our demand shifters to instrument for the wage, our estimated parameter increases to 1.781. Using the polynomial approximation, we estimate the equation, take derivatives with respect to the log wage, and find a mean labor supply elasticity of 0.019 (without demand shifters) and 2.746 (with demand shifters). We take this last specification as our preferred one. Both the linear and polynomial results are consistent with the rest of the literature on estimating labor supply. We further examine the properties of the estimated distribution of labor supply elasticities in Figure A.3. On the left panel, we plot means of ε^{L}_{Wjt} across quantiles of the labor market share distribution, while the right panel does the same across quantiles of the (log) markdown distribution. We see that the labor supply elasticity is declining in labor market shares, and strongly increasing in the markdown. These findings are consistent with oligopsonistic theories of labor market competition, where firms with greater market shares face lower labor supply elasticities, and are thus able to push (widen) markdowns further below 1. The findings in Figure A.3 show our estimated labor supply elasticities are well behaved and in line with the theory.

[74] We also report the mean labor supply elasticity by industry in Appendix Table A.9.

Table A.3 – Estimation of Labor Supply Elasticity

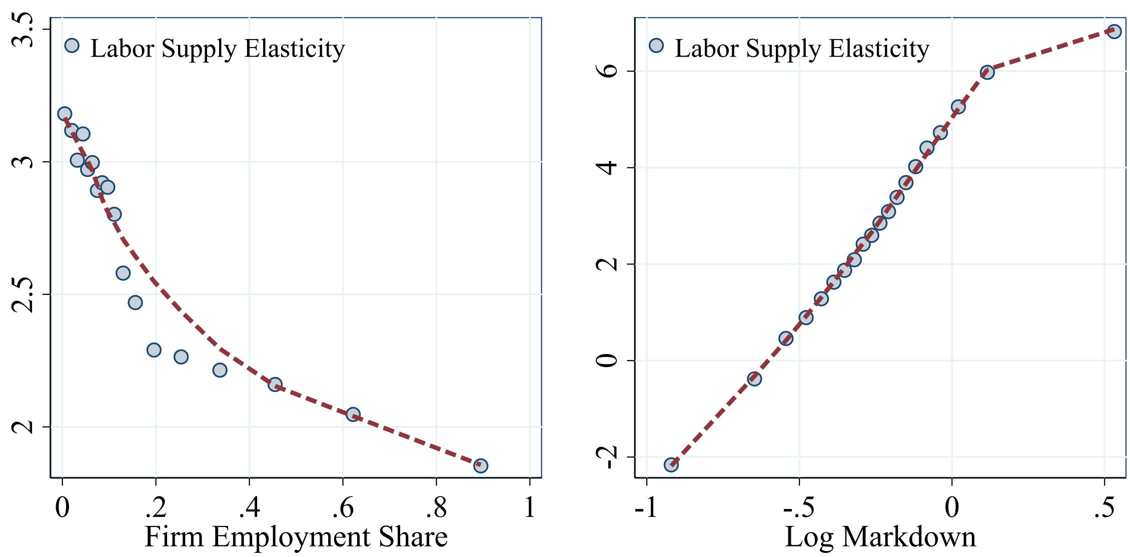
	Log-linear		Polynomial	
	OLS	IV	OLS	IV
$E(\varepsilon_W^L)$	0.053	1.781	0.019	2.746
	(0.006)	(0.044)		
R^2	0.527	0.411	0.539	0.529
Number of Observations: 374,000				

Note: Table A.3 shows regression coefficients from the labor supply elasticity estimation procedure described in section B.5. The instruments used in the IV regressions are ω_{jt-1} and η_{jt}. The first two columns show coefficients and standard errors (in brackets) from a set of linear regressions. The second two columns report the means of a distribution of estimates from a set of polynomial regressions. Number of observations rounded to the nearest thousand.

Figure A.3 – Market Share, Markdowns, and Labor Supply Elasticity

(A) Labor Supply Elasticity and Market Share

(B) Labor Supply Elasticity and Markdowns



Note: The left panel shows the relationship between the labor supply elasticity (y-axis) and market share (x-axis). The right panel shows the relationship between the labor supply elasticity (y-axis) and markdown (x-axis).

C Additional Results

Table A.4 – Workers' Characteristics

	Earnings	Wages	Hourly Wage	Age
Mean	51	56	38	38
Std. Dev.	37	117	162	13
P10	6	10	17	20
P25	25	38	27	28
P50	51	54	35	38
P75	67	69	44	48
P90	88	91	58	57
P99	165	177	149	66
Obs.		8,800,000		

Note: Table A.4 shows cross sectional moments of the distribution of workers in the sample. Annual earnings, annual wages, and hourly wages in thousands of 2010 USD. Number of observations rounded to nearest thousand.

Table A.5 – Firms' Characteristics

	Employment	Revenue	Value Added	Value Added per worker	Firm Age
Mean	24	6,191	1,993	86	16
Std. Dev.	202	57,549	14,946	106	11
P10	2	289	114	33	5
P25	3	494	197	51	7
P50	6	1,024	404	74	14
P75	14	2,722	1,018	104	22
P90	36	8,440	2,908	147	30
P99	281	83,647	26,531	298	50
Obs.			374,000		

Note: Table A.5 shows cross sectional moments of the distribution of firms in our sample. Revenue, value-added, and valued-added per worker are in thousands of 2010 USD. Number of observations rounded to nearest thousand.

Table A.6 – Firm Size and Firm Age Distributions

Firm Size Employment	Firms Share (%)	Employment Share (%)	Firm Age Years	Firms Share (%)	Employment Share (%)
1 to 4	40.19	4.14	3	3.73	2.55
5 to 9	24.46	6.91	4	6.14	4.33
10 to 19	16.96	9.74	5	5.92	4.08
20 to 99	15.00	25.58	6 to 10	22.64	17.89
100 to 1,000	3.20	33.01	11 to 15	16.92	13.43
1,000+	0.20	20.62	16 to 20	15.12	14.1
			21+	29.51	43.62

Note: Table A.6 shows cross sectional moments of the distribution of firms in the sample by size and age groups.

Table A.7 – Cross-Sectional Model Estimates by Industry

	Wages and Markdowns			Output Elasticities			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industries	$\log W_{jt}$	$\log MRPL_{jt}$	μ_{jt}	RTS_{jt}	ε^Y_{Kjt}	ε^Y_{Ljt}	ε^Y_{Mjt}
Mining and Quarrying	6.72	7.29	0.61	0.96	0.05	0.33	0.59
Manufacturing	6.63	6.88	0.80	0.97	0.05	0.38	0.53
Construction	6.60	6.81	0.84	0.94	0.05	0.38	0.51
Wholesale and Resale	6.56	6.79	0.84	0.96	0.04	0.25	0.67
Transportation and Storage	6.63	6.91	0.79	0.93	0.06	0.41	0.46
Accommodation and Food	6.49	6.84	0.74	0.92	0.06	0.35	0.52
Information and Comm.	6.69	6.80	0.94	0.96	0.06	0.45	0.45
Finance and Insurance	6.57	6.77	0.87	0.96	0.06	0.43	0.47
Real Estate	6.58	6.92	0.77	0.91	0.07	0.40	0.45
Professional, Scientific, Tech.	6.62	6.82	0.85	093	0.06	0.48	0.39
Admin and Support Services	6.62	6.85	0.84	0.93	0.06	0.47	0.40
Other Services	6.56	6.86	0.77	0.93	0.05	0.36	0.52

Note: Table shows the means of the model estimates by industry.

Table A.8 – Moments of TFP distribution estimated without adjusting for ability

Variables	ν^L_{jt}	η^L_{jt}	ϵ^L_{jt}
Mean	0.00	0.01	-0.01
Std. Dev.	0.26	0.08	0.19
p10	-0.28	-0.07	-0.21
p25	-0.14	-0.03	-0.12
p50	0.00	0.01	-0.03
p75	0.14	0.04	0.08
p90	0.30	0.08	0.22
p99	0.72	0.22	0.60
Obs.		374,000	

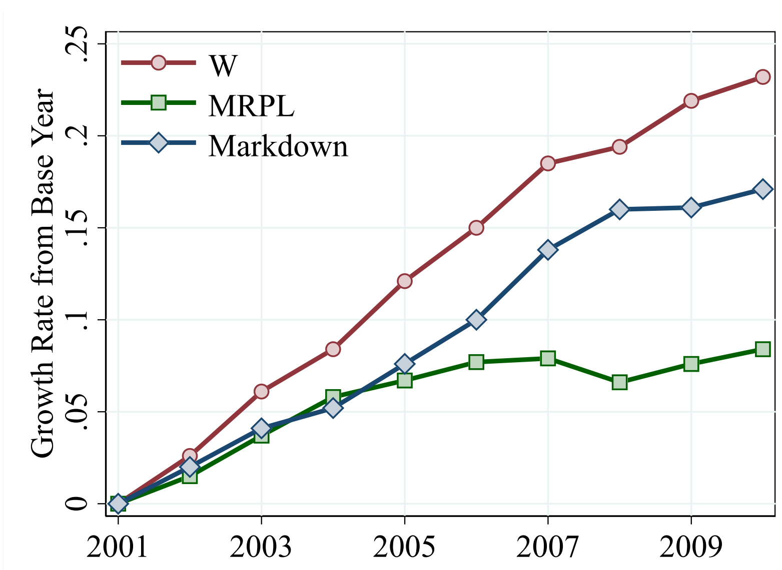
Note: Table A.8 shows cross sectional moments of the model estimates. Number of observations rounded to nearest 000s.

Table A.9 – Passthrough Elasticities and Labor Supply Elasticities by Industry

	Wages and Markdowns			
	(1)	(2)	(3)	(4)
Industries	ε_{η}^{W}	$\varepsilon_{\eta}^{MRPL}$	ε_{η}^{μ}	ε_{W}^{L}
Mining and Quarrying	0.28	2.10	-1.82	2.98
Manufacturing	0.26	1.96	-1.70	3.33
Construction	0.37	2.12	-1.75	3.09
Wholesale and Resale	0.32	2.34	-2.02	2.63
Transportation and Storage	0.44	2.17	-1.72	3.27
Accommodation and Food Services	0.45	2.75	-2.29	1.02
Information and Communication	0.38	1.93	-1.55	3.69
Finance and Insurance	0.36	1.91	-1.55	1.27
Real Estate	0.44	2.42	-1.98	1.61
Professional, Scientific and Technical	0.40	2.08	-1.68	3.45
Administrative and Support Service	0.42	2.22	-1.80	3.27
Other Services	0.35	2.27	-1.92	2.94

Note: Table shows the means of the estimated passthrough elasticities of passthrough from TFP shocks (η) to wages (column 1) to MRPL (column 2), and to markdown (column 3) by industry. Column 4 shows the means of estimated labor supply elasticities by industry

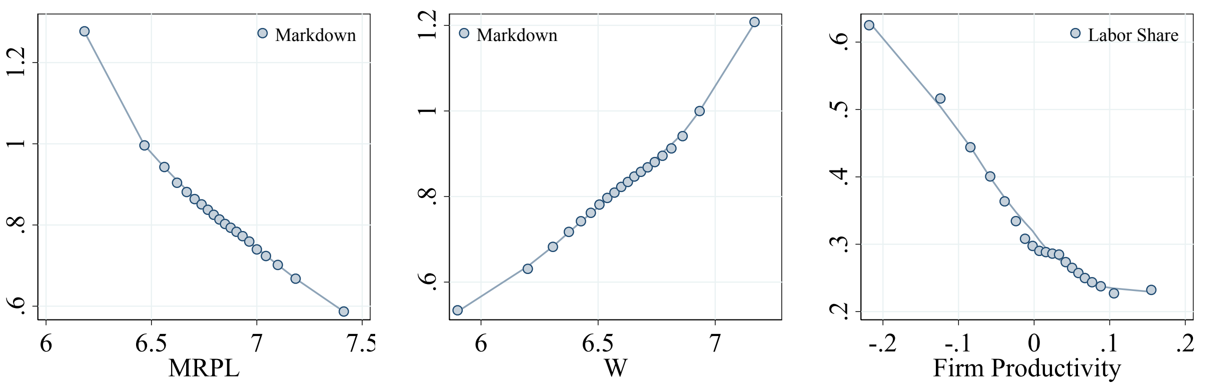
Figure A.4 – Wages, Markdown, and Firm Productivity over time



Note: This figure shows the time series of the component of wages relative to 2001.

Figure A.5 – Correlation of Markdowns and Labor Shares with Productivity and Wages

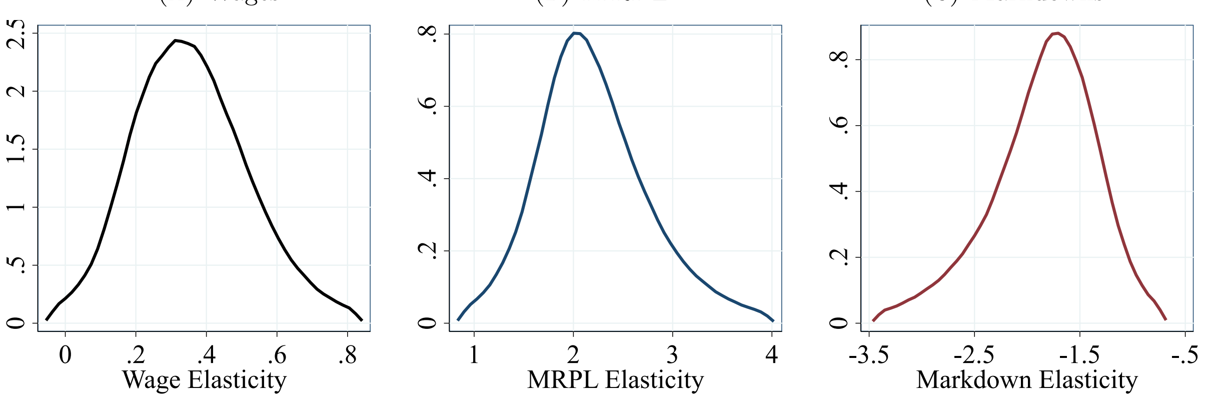
(a) Markdown and MRPL (b) Markdown and Wages (c) Labor Shares and Productivity



Note: This figure shows binscatter plots of firm-level markdowns by equal-sized groups of firm productivity (ω_{jt}), labor share of revenue, and mean worker ability, based on a sample of approximately 374,000 firms-year observations. Productivity and worker ability are in logs, while labor shares and markdowns are in levels.

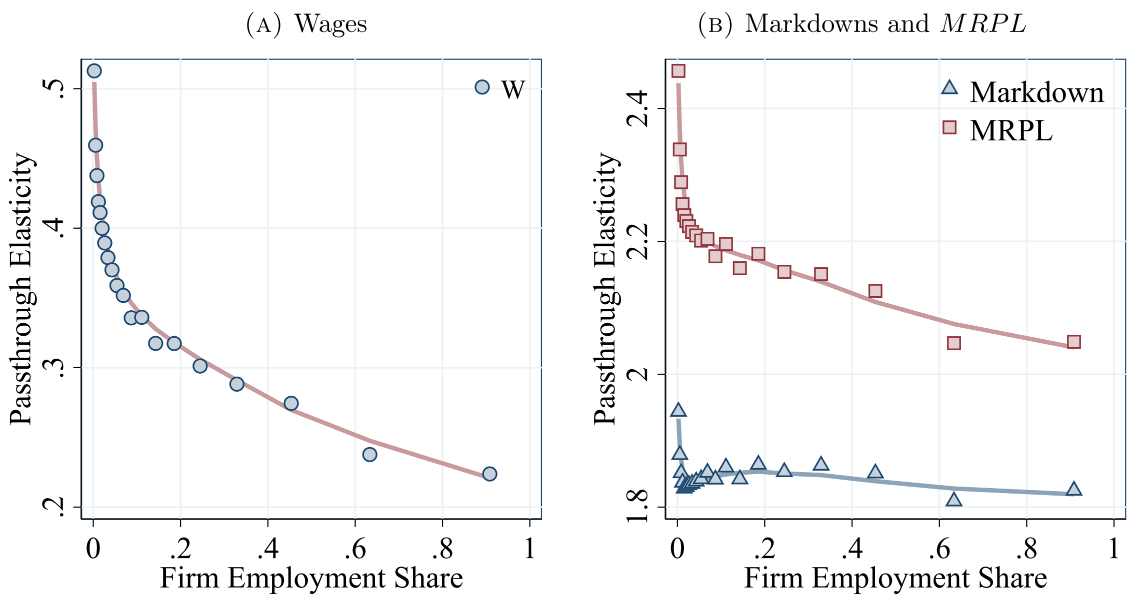
Figure A.6 – Distributions of Firm-Level Passthrough Elasticities

(a) Wages (b) $MRPL$ (c) Markdowns



Note: This figure shows density plots for the polynomial estimates of the passthrough elasticities from a persistent shock to firm TFP, η_{jt}, to wages, markdowns, and MRPL. All density plots exclude the top and bottom percentiles of their respective distributions.

Figure A.7 – Passthrough by Firm Employment Share



Note: This figure shows binscatter plots the average passthrough to firm-level markdowns (in absolute value), MRPL, and wages from a persistent shock to firm TFP, η_{jt}, within firm employment share groups, based on a sample of approximately 374,000 firms-year observations. Employment share is the fraction of workers hired by a particular firm within a year/industry/municipality bin, where industries are defined by 4-digit NACE codes.